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Review article

A survey on unsupervised learning for wearable sensor-based activity recognition

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ABSTRACT

Human Activity Recognition (HAR) is an essential task in various applications such as pervasive healthcare, smart environment, and security and surveillance. The need to develop accurate HAR systems has motivated researchers to propose various recognition models, feature extraction methods, and datasets. A lot of comprehensive surveys have been done on vision-based HAR, while few surveys have been done on sensor-based HAR. The few existing surveys on sensor-based HAR have focused on reviewing various feature extraction methods, the adoption of deep learning in activity recognition, and existing wearable acceleration sensors, among other areas. In recent times, state-of-the-art HAR models have been developed using wearable sensors due to the numerous advantages it offers over other modalities. However, one limitation of wearable sensors is the difficulty of annotating datasets during or after collection, as it tends to be laborious, time-consuming, and expensive. For this reason, recent state-of-the-art activity recognition models are being proposed using fully unlabelled datasets, an approach which is described as unsupervised learning. However, no existing sensor-based HAR surveys have focused on reviewing this recent adoption. To this end, this survey contributes by reviewing the evolution of activity recognition models, collating various types of activities, compiling over thirty activity recognition datasets, and reviewing the existing state-of-the-art models to leveraging fully unlabelled datasets in activity recognition. Also, this survey is the first attempt at a comprehensive review on the adoption of unsupervised learning in wearable sensor-based activity recognition. This will give researchers in this area a solid background and knowledge of the existing state-of-the-art models and an insight into the grand research areas that can still be explored.

Contents

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Nomenclature

AAE	Adversarial Autoencoder
AAL	Ambient Assisted Living
AST	Arm Skin Temperature
BSAL	Bayesian Stream-based Active Learning
CASAS	Center of Advanced Studies in Adaptive System
CID	Complexity Invariant Distance
CFR	Correlative Feature Selection
COR	Correlation-based dissimilarity
CRBM	Conditional Restricted Boltzmann Machine
CRF	Conditional Random Fields
CST	Chest Skin Temperature
DBN	Deep belief Network
DSADS	Daily and Sports Activities Data set
DTW	Dynamic Time Warping
DWT	Discrete Wavelet Transform
EM	Expectation Maximization
EUCL	Euclidean Distance
GMM	Mixture of Gaussian
GSR	Galvanic Skin Response
HAC	Hierarchical Associative Classifier
HAR	Human Activity Recognition
HIER	Average-Linkage Hierarchical Agglomerative Clustering
HMM	Hidden Markov Model
IIC	Invariant Information Clustering
IGGM-GAN	Infinite Gaussian Mixture Model Generative Adversarial Networks
LDA	Latent Dirichlet Allocation
MDN	Mixture Density Network
MHMMR	Multiple Hidden Markov Model Regression
NAT	Near-body Ambient Temperature
NCD	Normalized Compression Distance
OTC	Open then Close
OTO	On then off
PACF	Autocorrelation based dissimilarity
PCA	Principal Component Analysis
PDC	Permutation Distribution Clustering
PER	Periodogram-based distances
SAE	Stacked Autoencoder
SimCLR	Simple Contrastive Learning
TPN	Transformation Prediction Network
WGAN	Wasserstein Generative Adversarial Network

1. Introduction

Human Activity Recognition (HAR) is a branch of research aimed at defining and testing novel approaches for accurately recognizing human activities using signals [1]. State-of-the-art activity recognition systems can be developed using datasets obtained through vision-based and sensor-based devices [2,3]. Early research on activity recognition, such as [4–6], focused primarily on vision-based activity recognition, and this method was able to develop systems that are capable of effectively recognizing activities. The vision-based dataset is obtained by placing a capturing device such as cameras in strategic positions to capture the activities of entities in the environment. However, with this method, the subject may choose to interact with the system or not. Also, the camera-based solution may not function in particular cases where continuous monitoring of a person's activity is required. Furthermore, cameras are intrusive, and many people are uncomfortable with being constantly monitored by cameras.

Sensor-based activity recognition is used as a result of these issues. Sensor-based data is typically made up of time series of state changes and various parameter values, which are frequently combined and processed for activity recognition using data fusion, probabilistic or statistical analytic methods, and formal knowledge technologies [7]. In recent times, object sensors, environmental sensors and wearable sensor devices have been widely accepted in our everyday life. Wearable sensors involve attaching physical sensors to humans in a way that the human is still able to perform all necessary activities without infringements. Wearable sensors use inertia measurement units and Radio Frequency Identifications to collate the subject's activities. While environmental sensors often use various modes of sensors to observe and gather the activities between a subject and the entities in the subject's immediate environment. Unlike cameras, sensors have the advantage of monitoring activities on a virtual basis and are not constrained to a narrow observation space [8].

Several researchers, as seen in [9–11], among others, have carried out HAR research through datasets obtained through wearable sensors. The work of [12,13] have developed activity recognition systems through environmental sensors data, while [14–16] have carried out activity recognition research through the hybrid sensors. Hybrid sensors involve the fusion of data obtained through the wearable, object, or environmental sensors. However, recent HAR research works have focused on developing recognition models using datasets obtained through wearable sensors. This is because wearable sensors are relatively cheaper and easier to deploy than other modalities of sensors. Examples of wearable sensors include accelerometers, magnetometers, and gyroscopes, among many others. Recent advancements in miniaturization have enabled the embedding of these sensors into smartwatches, smartphones, and other wearable devices that are affordable and easier to deploy, therefore eliminating the challenges associated with users' privacy. This has motivated researchers to collect activity data using these wearable devices.

The importance of HAR to our daily lives cannot be overemphasized. HAR is one of the emerging areas that have garnered the interest of researchers from various fields because its application cuts across various research areas. Example of such areas are; mobile computing [17,18], context-aware computing [19], pervasive computing [20], Ambient Assisted Living (AAL) [21–24], surveillance systems [25,26] and most recently in serious games [27]. The most practical deployment of HAR has been in fall detection [28], behavioural monitoring [29], psychological monitoring [30], stress detection [31], gait anomaly detection [32,33] and others. HAR computation is very demanding because each of the obtained data must be processed independently [34]. Before data can be processed to infer activities, activity modelling is needed. Activity modelling can be done through the knowledge-driven approach or the data-driven approach. Earlier works on HAR have proposed the knowledge-driven approach to developing HAR systems. By exploiting extensive prior information on the topic of interest, knowledge-driven techniques construct activity models directly using knowledge engineering and management tools [35]. Data-driven approaches use data mining and machine learning methods to generate activity models from large-scale datasets of users' activities [36]. This is quite efficient than the knowledge-driven approach because they can handle ambiguous and temporal data.

Wearable sensor-based activity recognition is a complicated field with a broad scope, and the need to have accurate HAR systems have motivated researchers to proposing various models, feature extraction techniques, datasets, and other data driven approaches. Despite the various advantages of obtaining data with wearable sensors, annotating the collected data is quite laborious, time-consuming and expensive. The complexity of labelling wearable sensor datasets has motivated researchers to propose activity recognition models using fully unlabelled datasets. To do this, there is a need to learn the underlying structure of the wearable sensor-dataset before recognition. This approach is termed unsupervised learning, which is mostly used for exploratory data analysis in order to find patterns in data [37].

The concept and processes of activity recognition using wearable sensors is quite broad. Therefore, to understand its concept, state-of-the-art approaches and future directions, several extensive survey papers such as Wang et al. [38], Mao [39], Jian and Yian [40], Patel and Shah [41], and Chen et al. [7], among others, have been written. However, the existing literature on sensor-based HAR is insufficient due to its wide scope and applicability in various domains. Also, no existing sensor-based surveys have carried out an in-depth review of the recent adoption of unsupervised learning in wearable sensor-based HAR. This survey paper aims to contribute by reviewing existing literature on wearable sensor-based HAR, identifying some areas that were not well addressed in existing survey papers, and then using such information to form sufficient background and discuss emerging trends in wearable sensor-based HAR research. In order to form a basis for this survey, we research existing survey papers on Wearable Sensor-based Human Activity Recognition from various libraries and databases such as Scopus, IEEExplore, Science Direct, Web of Science and ACM. Table 1 shows some existing survey papers selected based on their contributions and topics not well discussed.

In the existing surveys shown in Table 1, some major aspects of wearable sensor-based HAR have been covered; however, none focused on the recent trend of adopting unsupervised learning in wearable sensor-based HAR. In Chen et al. [37], a brief discussion was provided on unsupervised learning for HAR, but it was not the focus of the authors. Also, in Colpas et al. [36], the survey focused on unsupervised learning, but only reviewed the methods used in achieving effective clustering in wearable sensor-based HAR. Therefore, this paper surveys the state-of-the-art unsupervised methods for wearable sensor-based activity recognition. Specifically, the contributions of this paper are summarized as follows:

i. We first delve into the evolution of wearable sensor-based HAR and present some HAR systems developed through wearable sensor datasets,

ii. Secondly, we compile a list of thirty-three (33) existing wearable sensor-based datasets in HAR and their properties,

iii. Thirdly, we discuss the emerging trends of adopting unsupervised learning in wearable sensor-based human activity recognition and the existing state-of-the-art in wearable sensor-based HAR,

iv. Lastly, we present the existing state-of-the-art methods in addressing issues relating to data imbalance in wearable sensor-based HAR data through clustering and data augmentation and also, we discuss some future research directions.

The rest of this paper is organized as follows: In Section 2, we provide a brief survey on the evolution of wearable sensor-based HAR and the types of wearable sensors used in activity recognition. In Section 3, the general framework of HAR is presented, the applicability of HAR is discussed, and thirty-three wearable sensor-based datasets are compiled. Section 4 discusses unsupervised learning in wearable sensor-based HAR, together with the clustering and data augmentation approaches employed. Section 5 presents some grand areas and future research directions that wearable sensor-based HAR researchers can explore, while Section 6 concludes.

2. Evolution of wearable sensor-based HAR

Prior to research on HAR and its applications, researchers focused on image recognition systems. Image recognition systems are quite simple to model and develop when compared to activity recognition systems. HAR involves collecting and interpreting moveable objects' data to recognize their behaviours. Early works on HAR can be traced back to the late 1990s, as seen in [51,52]. However, the need to improve accuracy under more realistic conditions has led to the constant development of various techniques. Recently, several researchers have proposed HAR systems for smart homes [53–55], physical and mental wellbeing [22,56,57], among other areas, which are later discussed in this paper.

As mentioned earlier, state-of-the-arts HAR systems can be developed using datasets obtained through vision-based [44,58–60] and sensor-based devices [2,3], and the limitations of vision-based brought about the advent of the sensor-based method, whose data are in time-series format. A taxonomy of this is shown in Fig. 1. The concept of employing sensors to monitor and recognize activity has been around since the early 2000s where Philipose [61] worked on a large scale human activity recognition using ultra-dense sensing, and in Wilson and Atkeson [62] where simultaneous tracking and activity recognition was proposed using binary sensors; although some researchers already adopted sensors in other related fields such as home automation since the late 1990s as seen in [63]. Research during this period had already focused on the deployment of wearable sensors and environmental sensors.

Sensor-generated data is favoured over vision-generated data in HAR applications due to various advantages such as low power, small size, low cost, and convenience. As presented in Fig. 1, sensors can either be environmental, object or wearable. Environmental sensors are typically placed throughout the environment to collect precise data on basic environmental characteristics such as human's interaction with objects, humidity and temperature [47]. When human activities occur, the environmental sensors track the changes in the environment and then recognize the activities [64]. Several publicly available datasets are obtained through environmental sensors, and various researchers have developed HAR systems through such datasets. An example is in [12], where a dataset consisting of 28 days of environmental sensor data and its annotation was used, and various experiments were conducted to prove how the Hidden Markov Model and conditional random fields perform in recognizing activities.

In wearable sensor-based activity recognition, the sensors are attached to subjects. Wearable sensors involve attaching physical sensors to humans in a way that the human is still able to perform all necessary activities without infringements. Recent advancements in miniaturization [65,66] and nanotechnology [67] have led to the embedding of sensors into wearable devices, and this has brought about a whole new level to wearable sensor technology. Sensors can be incorporated into clothing, eyewear, wristwatches, mobile devices, or placed on the body directly. As a result, they are much easier to move around with, cheaper to obtain and deploy, and can capture activities over a wide area. Generally, they can track body posture and movement, among other numerous functions.

Table 1
A brief description of some existing survey papers on sensor-based activity recognition.

Survey paper	Year	Topics focused on and elaborated
Chen et al. [7]	2012	The evolution and current state of wearable sensor-based activity recognition, as well as the distinction between data-driven and knowledge-driven approaches
Lara & Labrador [2]	2013	Using wearable sensors to create an AR dataset, a two-level taxonomy based on supervised and semi-supervised learning, and concerns and challenges with wearable sensors are all discussed.
Nweke et al. [42]	2018	The goal of this review was to give comprehensive descriptions of deep learning algorithms for recognizing human activity from mobile and wearable sensors.
Emiro et al. [43]	2018	A review on existing wearable sensor-based datasets used in evaluating Human Activity Recognition Systems.
Wang et al. [38]	2019	Deep learning in wearable sensor-based HAR, as well as the combination of AR sensors, deep models and applications are the focus of this paper.
Prati et al. [44]	2019	The existing technologies and directions of wearable sensors, and how they are used for activity recognition
Patel & Shah [41]	2019	A review of several activity and behaviour analysis methodologies was conducted in order to identify seventeen key problems associated with sensor-based ambient assisted living systems.
Hussain et al. [45]	2019	Survey of work done in several domains of HAR from 2010 to 2018, with a focus on device-free solutions.
Suresha et al. [46]	2020	Convolutional neural networks (CNNs) and related pipelines are used to investigate features, some fusion procedures, and their results. Also covered were multi-model approaches for extracting cues and score fusion strategies in hybrid deep learning systems.
Dang et al. [47]	2020	The classification of HAR methods and a review on the utilization of deep learning in HAR
Colpas et al. [36]	2020	The clustering technique was utilized to identify information in HAR on unsupervised datasets, as well as the description of high-value factors such as the year of publication, article type, most commonly used algorithms, and dataset categories.
Kumar & Chauhan [48]	2021	Presented existing deep learning approaches for the recognition of sensor-based human behaviour and suggested a new taxonomy to arrange deep learning techniques according to the challenges solved.
Liu et al. [49]	2021	Presented a general review of healthcare applications that made use of wearable sensors, discussed the use of classical machine learning in wearable sensor-based HAR, and the general supervised learning approach.
Ferrari et al. [50]	2021	The survey looked at potential solutions for each wearable sensor-based HAR task, including data gathering, pre-processing, data segmentation, feature extraction, and classification. The study also highlighted few current smartphone datasets and provided various criteria commonly used to assess a classifier's effectiveness.
Chen et al. [37]	2021	A study on deep learning was presented, with an emphasis on existing methodologies that can be combined with deep learning approaches to address various wearable sensor-based HAR system difficulties.

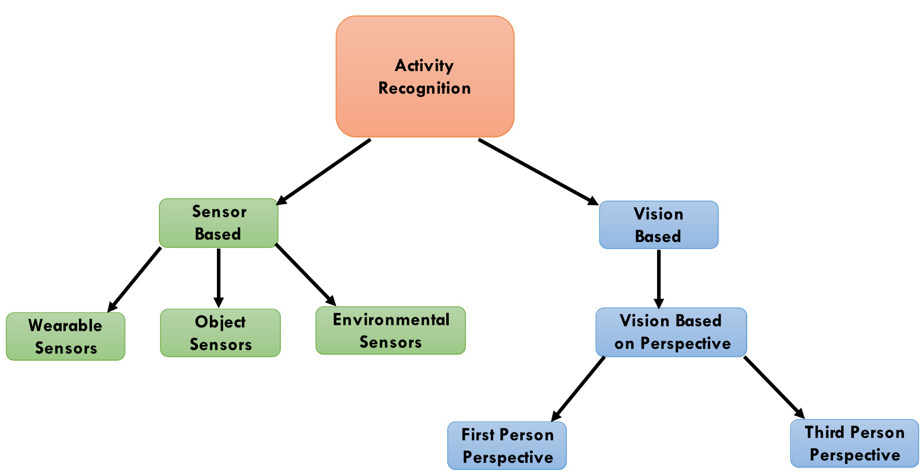

Fig. 1. Taxonomy of HAR methods.

Researchers such as Banos et al. [68], Scheurer et al. [69] and Zhu et al. [10], among others, have developed HAR systems using wearable sensors, with the most common sensor device being an accelerometer. An accelerometer is a device that measures the acceleration of an entity. Other examples of sensor devices include Smartwatches, Electrocardiography monitors, Biosensors, and Smart shirts, as seen in Table 2. Since most humans wear wristwatches and carry smartphones, obtaining activity data through this method is relatively easy. Most recently, some researchers, as seen in [3,70–72], among many others that are later discussed in this paper, have proposed the use of wearable sensors to obtain human activity data. An example of this is in Ronna and Cho [73], where the authors utilized the inherent properties of activities and 1D time-series signals and used a deep

Table 2
Sensor devices and examples ([74]).

S/N	Class	Sensor
1	Inertial sensors	Accelerometer [75–77] Gyroscope [78,79] Magnetometer [78]
2	Environmental sensors	Temperature [17] Humidity [80] Barometer [81]
3	Physical health sensors	Electrocardiogram [82] Electroencephalograph [83] Electromyogram [84]

Table 3
Application of HAR.

S/N	Domain	Paper
1.	Elder healthcare	[81,89,90]
2.	General healthcare	[29]
3.	Home assistance	[91,92]
4.	Shopping experience	[93]
5.	Military	[94]
6.	Sport	[95]

convolutional neural network to develop HAR using smartphone sensors.

3. General framework

HAR can be applied to several fields such as medical, military, agriculture, security, among others. Most recently, diabetes and heart disease patients are mandated to follow a particular exercise routine to aid their healing process. The movements of these patients are monitored by AR systems, which later give feedback to their caregivers [85]. Another common application of AR in the medical sector is in monitoring dementia and other brain-related diseases by having their movements monitored [86]. An example of this is in [87], where the authors modelled the routine activities of dementia patients and used the AR system to monitor any deviation from such routine. The authors adopted a hierarchical approach to determine abnormalities in dementia patients' activities using Markov Logic Network. In [22], the authors developed a Nurse care system to monitor the patients in hospitals using a convolutional neural network (ConvNet). The versatility of HAR is also evident in [88], where the authors proposed a HAR system to monitor oil well drilling activities. The researchers combined Fuzzy Rule-Based and Random Forest Classifiers to develop a novel hierarchical classifier. Table 3 shows an extract of other areas where HAR has been applied.

The performance of recognition systems depends on various factors such as; the activity set, the quality of obtained data, the feature extraction method, and the learning algorithm [2]. Data collection, feature encoding, model optimization, and prediction comprise the activity recognition chain. The choice of categorization models and the researcher's choice of data encoding heavily influences the performance of HAR [96].

Wearable sensor-based monitoring data is often a time series of state changes and various parameter values that are widely processed for activity recognition using data fusion, probabilistic or statistical analytic approaches, and formal knowledge technologies [7]. In some cases, a stand-alone wearable sensor may not be able to handle some complicated physical motions and multiple environmental interactions. For example, an accelerometer can monitor acceleration but not positional changes, transitional movements, or other movements. Likewise, a gyroscope can monitor positional changes and general direction, but not acceleration. Because of this, there is a need to deploy and fuse multiple sensors to obtain accurate data for efficient HAR systems. For example, experiments in Bharti et al. [97] deployed hybrid sensing to recognize indoor activities and achieved an accuracy of 95%. Also, in Lago et al. [98], the researchers trained a HAR system with data obtained through multiple datasets and tested the system with a single sensor-based HAR dataset. A comparison of a few existing HAR research carried out through single sensing devices, and multiple sensing devices is presented in Tables 4 and 5.

Researchers embraced the use of a single device due to its simplicity and the freedom it affords to the subjects to carry out their activities. As shown in Table 4, HAR systems can record satisfactory accuracy when trained with single sensor data [99]. However, there are situations where a single sensor cannot obtain the needed data. For example, a subject opens a door and then climbs the stairs. Situations such as this have led to the use of multiple sensors to obtain activity data, as seen in [100,101], among others. Generally, multiple sensing devices are used to recognize complex activities (activities of daily living). For example, wearable devices attached to the wrist allow the hand motion to be captured, and the wearable device on the waist is used to capture the body motion. Both information is fused to recognize complex activities. Another example is when a wearable device on the waist is used together with environmental sensors; the wearable allows the basic activities e.g. walking and standing to be recognized, while the environmental sensors capture the user-object interaction, which is to be fused to recognize complex activities. Examples of literature that have carried out HAR research works using multiple sensing devices are shown in Table 5.

As seen in Table 5, most researchers combined accelerometers with other ambient sensing devices such as gyroscopes, which can accurately detect the subject's body orientation and posture [44]. The typical process of wearable sensor-based HAR consists of three crucial stages: data segmentation, feature extraction and recognizing the type of activity, as shown in Fig. 2. All phases of the HAR process have been subjected to extensive research. Each phase is discussed in detail in other sections. Generally, wearable sensor-based HAR datasets consist of sensor data streams collected from single or multiple persons [102,103]. A compilation of some existing datasets obtained through wearable sensors and the fusion of wearable sensors with other sensors and their details is presented in Table 6. Investigation of the number of research papers that have benchmarked their models using each dataset was also carried out on various databases, through google scholar, using relative keywords. The result is shown in Table 6. While those that could not be ascertained due to their generic names were represented as "undefined".

3.1. Wearable sensor datasets

Generally, wearable sensor-based HAR datasets consist of sensor data streams collected from single or multiple persons [102, 103]. A compilation of some existing datasets obtained through wearable sensors and the fusion of wearable sensors with other sensors and their details is presented in Table 6. It is shown that PAMAP2 is the most used dataset, with four hundred and forty two (442) papers benchmarked on the dataset, while WISDM, UCI-HAR and Opportunity have four hundred and nineteen (419), two hundred and ninety seven (297), and two hundred and fifty three (253) papers respectively. REAL-DISP dataset has a total of 30 different activities, which is the highest among the datasets collated, and has been used for model benchmarking in 51 papers. As shown in the table, accelerometer and gyroscope are the most used sensors as they were combined for data collection in eighteen of the collated thirty three datasets, while accelerometers

Table 4
Existing HAR research works done with Single Wearable Device.

Author	Year	Sensor location	Recognized activities	Methods	Accuracy
Ravi et al. [104]	2005	3D accelerometer around Pelvic Region	Standing, Walking, Running, sit-ups, vacuuming	Naive Bayes, KNN, SVM, Binary Decision	99.3
Allen et al. [105]	2006	3D accelerometer around the waist	Sitting, lying, walking and transitions	Gaussian Mixture Model	91.3
He [99]	2010	A 3D accelerometer in the trouser	Jumping, walking, running, standing	Wavelet Autoregressive Model	95.45
Xiao &Liyu [100]	2015	3D accelerometer and 3D Gyroscope	Running, standing, walking, falling	Non-linear Kernel Discriminant, Analysis and Extreme Learning Machine	99.81%
Wang et al. [101]	2016	Tri-axial accelerometer and built-in gyroscope smartphone	Walking, sitting, lying, standing	K-Nearest Neighbour	87.8%

Table 5
Some HAR research works that adopted multiple devices for data collection.

Author	Year	Sensor location	Recognized activities	Methods	Accuracy
Ermeset al. [106]	2008	Two 3D accelerometers placed on the hip and wrist + GPS	Sitting, standing, walking, running, cycling, rowing, playing football	Decision tree	89%
Mannini & Sabatini [107]	2010	Five 2D accelerometers placed on the hip, wrist, arm, ankle and thigh	Climbing, walking, running, sitting, standing	HMM	98.5%
Aziz et al. [108]	2013	Four 3D accelerometers were placed on the sternum, left ankle and right ankle	Fall detection, standing	Linear Discriminant Analysis	89%
Jia & Liu [109]	2013	3D accelerometer on the waist and ECG on the chest	Sitting, standing, walking, running	Linear Discriminant Analysis and Relevance Vector Machines	99.57%
Noor et al. [110]	2018	Accelerometer on the right side of users' waist, and various ambient sensors positioned in strategic places	Walking, cooking, having a meal, washing dishes, watching TV, and others	Ontological Modelling	91.5%
Shaikh et al. [111]	2018	3D accelerometer and two Force Sensitive Resistors	Walking gait detection	Finite State Machine Modelling	98.9%

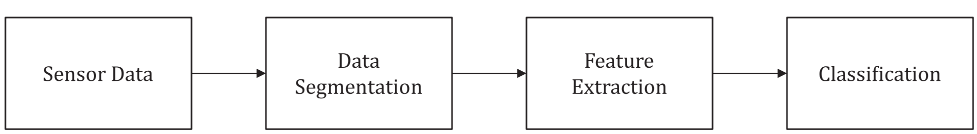

Fig. 2. Typical process of sensor-based HAR.

only was used in nine of the datasets. The others combined accelerometers with other sensor devices.

Recognizing activities obtained through sensors has been an area of huge concern for HAR researchers. In general, human activities can be divided into basic and complex activities (activities of daily living). Basic activities can be further divided into static, dynamic and transitional activities. The various types of activities that can be performed by humans and their clusters are shown in Table 7.

3.2. Data segmentation

Data segmentation is done by dividing obtained data into smaller chunks called windows, which can be mapped to a particular activity [138]. The type of windowing, the size of the window, and the overlap between adjacent windows all influence window characteristics [50]. Activity-defined windows, event-defined windows, and sliding windows are the three basic types of windowing used in HAR [139]. The initial and end points of each window are picked by recognizing patterns of activity changes in activity-defined windows, whereas the window is constructed around a detected event in event-defined windowing. However, in the sliding window, data is divided into fixed-size windows with no gaps between them and, in certain circumstances, overlapped. An illustration of this is shown in Fig. 3. The sliding window is the most used segmentation method in HAR [140,141].

The size of the window directly impacts the segmentation accuracy, such that; windows should be large enough to ensure that at least one cycle of activity is contained and that comparable movements are distinguishable [142]. Once data segmentation

Table 6
Sensor-based Datasets and their characteristics.

S/N	Dataset	Sensor used	No. of Activities	Num. of Subjects	Applications	Features	No. of papers
1	UCIHAR [112]	Smartphone, Accelerometer, Gyroscope, Magnetometer	6	30	Locomotion	walking, upstairs, downstairs, laying, sitting, standing	297
2	WISDM [9]	Smartphone Accelerometer	6	36	Locomotion	Walking, upstairs, downstairs, Jumping, Sitting, Standing	419
3	OPPORTUNITY [113]	Accelerometer	18	12	Household activity recognition	Start, groom, relax, prepare coffee, drink coffee, prepare sandwich, eat sandwich, cleanup, break, OTC-fridge, OTC-dishwasher, OTC-door1, OTC-door2, lights OTO, Clean Table, Drink while Standing, Drink while sitting	253
4	UniMiB SHAR [114]	Smartphone Accelerometer	17	30	Fall Detection	Standing–laying, laying–standing, standing–sitting, running, sitting, downstairs, upstairs, walking, jumping, falling backward, falling forward, falling sideward, specific fall,	146
5	PAMAP2 [115]	Accelerometers, Magnetometers, Gyroscopes, and Heart Rate Monitors	18	9	Activity Recognition	Computer work, walking, ironing, lying, standing, nordic walking, house cleaning, sitting, vacuum cleaning, cycling, ascending stairs, descending stairs, descending stairs, folding laundry, running, watching tv, car driving, rope jumping, playing soccer	442
6	SCUT-NAA [116]	Tri-axial Accelerometer	10	44		Sitting, walking, walking quickly, walking backward, running, step-walking, jumping, upstairs, downstairs, cycling	22
7	HASC [117]	iPhone, iPod touch, WAA series (ATR)	6	10	Basic Activity Recognition	Stay, walk, jog, skip, upstairs, downstairs	45
8	AmLRepository: Ubisense, SmartFirst phase, SmartSecond phase [118]	RFID tags, localization sensors, accelerometers, gyroscopes, magnetometers, infrared motion capture sensors	6	5, 3, 5	Activity Monitoring	Walking, sitting, lying, standing, jogging, jumping	Undefined
9	UC Berkeley WARD [118]	Accelerometers, Gyroscope	13	20	Activity Recognition	Stand, sit, lie down, walk forward, walk left circle, walk right circle, turn left, turn right, upstairs, downstairs, jog, jump, push wheelchair	Undefined
10	USC-HAD [8]	Accelerometer, Gyroscope, Magnetometer, Galvanic Skin Response, Pulse Oximeter, Electrocardiogram, Barometric Pressure	12	14	Fitness Monitoring	Walking forward, walking left, walking right, walking upstairs, walking downstairs, running forward, jumping, sitting, standing, sleeping, elevator, elevator down	132
11	MIT PlaceLab Dataset [119]	Accelerometer, Wireless Heart Rate Monitor	5	1	Household activity recognition	Grooming/dressing, preparing meal, toilet/shower, washing dishes, doing laundry	63
12	CMU-MMAC [120]	Accelerometers, Gyroscopes, Magnetometer	5	43	Cooking activity recognition	Cooking brownies, pizza, sandwich, salad, scrambled eggs.	76
13	Singlechest [121]	Accelerometer	7	15		Working on Computer, standing up-walking-downstairs, standing, walking, Updownstairs, walking and talking, talking while standing	29

(*continued on next page*)

has been completed, the important features of the data can then be extracted.

3.3. Feature extraction

Once data has been collected under realistic conditions, pinpointing the most important attribute becomes vital. This process is called Feature Extraction, which is an important aspect of developing HAR systems. It entails filtering important information and obtaining details that allow signals to be compared [2]. The use of features rather than raw data has been shown to enhance classification accuracy in the literature [143]. Extracting features in wearable sensor-based HAR can be done in structural and statistical ways [144]. Structural extraction deals with the

Table 6 (*continued*).

S/N	Dataset	Sensor used	No. of Activities	Num. of Subjects	Applications	Features	No. of papers
14	Real-DISP [76]	Accelerometer, Gyroscope, Magnetic Sensor	33	17	Robust Activity Monitoring	Walking, jogging, running, jump up, jump front–back, jump-sideways, jump-legs-arms-open-closed, jump rope, trunk twist, waist bends forward, waist rotation, waist bend, reach heels-backward, lateral bend, lateral bend-arm, forward stretching, upper trunk-lower-body twist, arm lateral elevation, arm frontal elevation, frontal hand claps, frontal crossing of arms, shoulder high-rotation, shoulder low-rotation, arms rotation, knees-breast, heels-backside, crouching, knees-bending forward, rotation, elliptical bike, cycling	51
15	DaphNetFoG [122]	Accelerometer	3	10	Monitoring PD patient's walk, detection of freezing gait	No freeze (Stand, walk, turn), freeze	41
16	ActRecTut [123]	Accelerometer	12	2	Robust activity monitoring	Still, Opening window, closing window, watering plant, turning book pages, drinking from a bottle, cutting with a knife, chopping with a knife, stirring in a bowl, tennis forehand, backhand and smash	10
17	Nursing Activity [124]	iPod, Accelerometer	27	82	Nursing activity monitoring in the hospital	Vital, morning gathering, guest response, meal/medication, rehabilitation, outing response, oral care, morning care, get up assistance, excretion, daytime user response, change dressing, bathing, night care, washing, nighttime user response, emergency response, linen exchange, gods checking/preparation, medication organization, cleaning, handwriting recording, doctor visit correspondence, family/doctor visits, meeting, break	Undefined
18	HASC Corpus [125]	Smartphone, Smartwatch, Smartglass, Accelerometer	6	540	Basic Activity recognition	Stay, walk, jog, skip, upstairs, downstairs	Undefined
20	CASAS KYOTO (Testbed) [126]	Accelerometers, Gyroscope	11	20	Household activity monitoring	hygiene, sleep, bed-toilet, eat, work, exit home, relax, medications, shower	175
21	CASAS ARUBA [127]	Accelerometers, Door sensors, and Temperature sensors	11	7	Household activity monitoring	Medication, furniture moving, plant watering, playing game, making dinner, reading, gathering food, laundry, sweeping, setting table, bill paying	196
22	HASC BDD [128]	Accelerometer, Gyroscope	13	7	Dancing Activity Recognition	Dancing pose (Open Basic, Foot change, Fan, Hockey Stick, Newyork-Right, Newyork-Left, Turn, Natural Top, Opening Out, Alemana, Hand-Hand-Right, Hand-Hand-Left, Aida)	Undefined
23	AmL Energy Expenditure	Gyroscopes, Magnetometers, Accelerometers	16	10	Activities of daily living	Lying, sitting, standing, kneeling, all fours, doing dishes, computer work, lying-exercise, walking-light shores, floor scrubbing, digging, treadmill walk, treadmill run, light cycling, fast cycling	Undefined
24	Parkinson Disease [129]	Accelerometer, Compass Ambient light, Audio sensors	2	16	Monitoring Parkinson disease	Parkinson, Controlled	Undefined

(*continued on next page*)

interrelationship among data, while statistical extraction makes use of data characteristics for feature extraction. The accuracy of wearable sensor-based HAR systems depends majorly on the extracted features and their representation. Therefore, it is recommended that features must be perfectly extracted and represented.

Due to calibration problems, device malfunction, deployment issues, and various other issues, wearable sensor data frequently contains noise. De-noising helps in eradicating such issues. Examples of some de-noising techniques are the Linear filter [145] and the Kalman filter [146]. Fig. 4 shows the processes and feature extraction techniques possible in the wearable sensor-based datasets.

Table 6 (*continued*).

S/N	Dataset	Sensor used	No. of Activities	Num. of Subjects	Applications	Features	No. of papers
25	SKODA [130]	Accelerometer	10	1	Car maintenance activity monitoring	Writing, hood opening, hood closing, gaps checking, left-front door opening, left-front door closing, both left doors closing, trunk gap checking, open–close trunk, check steering	63
26	PPS Grouping [131]	Accelerometer, Gyroscope, Magnetometer, GPS, Microphone	2	10	Walking group formation detection	Walking together, Walking separately	Undefined
27	HCI [132]	Accelerometer	5	1	Leg Action Recognition	Flick kick, knee lift, jumping jack, superman jumps, high knee, feet back	Undefined
28	DSADS [133]	Accelerometer, Gyroscope, Magnetometer	19	8	Fitness Monitoring	Sitting, Standing, lying back-right, up and downstairs, standing still-elevator, moving-elevator, walking-parking lot, walking-treadmill, running-treadmill, exercise-stepper, exercise-cross trainer, cycling, rowing, jumping, playing basketball	22
29	MHealth [68]	Accelerometer, Gyroscope, Magnetometer	12	10	Activity Recognition	Standing still, sitting, laying down, walking, stairs climbing, waist forward, front arm raise, crouching, jogging, running, jumping	146
30	UjAml cup [134]	Smartwatch, Gyroscope, Magnetometer, other binary sensors	24	1	Household activity monitoring	Prepare breakfast, cook lunch, cook dinner, eat breakfast, lunch, dinner, eating snacks, watching TV, Enter a smartlab, playing video game, relax on sofa, exit smartlab,visit smartlab, use waste bin, wash hands, brush teeth, use toilet, wash dishes, laundry, table work, dressing, wake up, sleep	30
31	Sussex Huawei Locomotion Dataset [135]	Smartphones Accelerometer, Gyroscope, Magnetometer	8	3	Activity Recognition	Still, walk, run, bike, car, bus, train, subway	137
32	WHARF [136]	Accelerometer	14	17	Household activity monitoring	Toilet, get up-bed, laying-bed, sit-chair, stand up from chair, feeding, drink, eat-fork and knife, eat-spoon, pour water-glass, use telephone, upstairs, downstairs, walk	15
33	KU-HAR [137]	Smartphone, Accelerometer, Gyroscope	18	90	Activity monitoring	Stand, sit, lay, pick, jump, walk, run, talk-sit, talk-stand, stand-sit, lay-stand, push-up, sit-up, walk-backward, walk-circle, upstairs, downstairs, table tennis	7

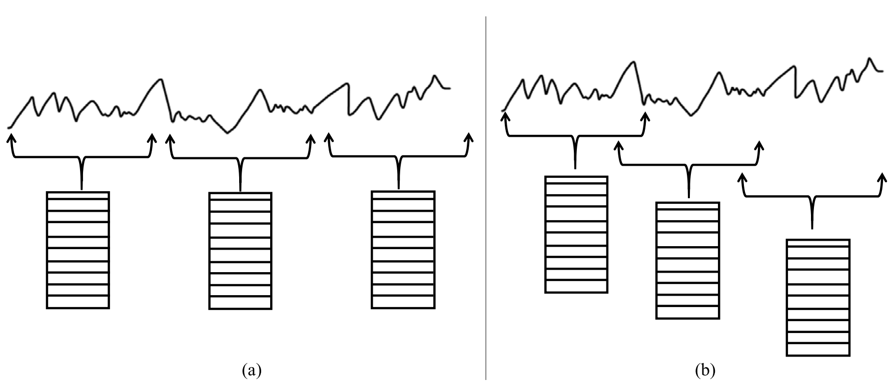

Fig. 3. Sliding window illustration (a) Windowing without overlap (b) Windowing with overlap.

Feature extraction is important to identify elements from pre-processed data based on distinguishing factors such as signal frequency and phase. Generally, a feature can be extracted in two ways; hand-crafted extraction and automatically learned feature extraction. Hand crafted features involve an expert selecting the features based on heuristics.

3.3.1. *Hand-crafted feature extraction*

Hand-crafted or manual feature extraction in the sensor-based dataset can be classified into frequency-domain, time-domain and wavelet-domain approaches based on signal qualities [47]. In the time-domain approach, time-domain features are derived based on the amplitude variations of signal over time, median, variance, mean, range, and skewness [70]. Time Domain Features

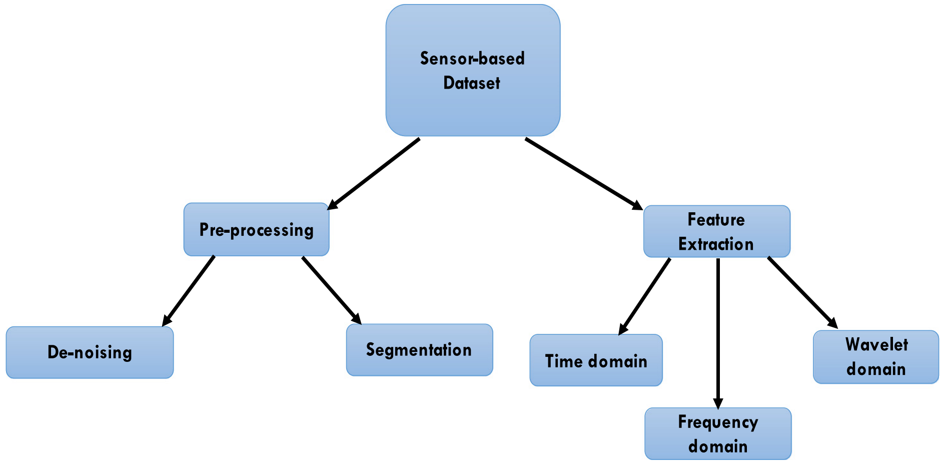

Fig. 4. Sensor-based dataset processing and feature extraction.

Table 7
A generic cluster of activities recognized by HAR Systems ([2]).

S/N	Cluster	Description
1	Ambulation	Walking, Running, Sitting, Standing, Climbing stairs, Descending stairs, Riding escalators and elevators
2	Daily activities	Eating, Drinking, Sleeping, Reading, Watching TV
3	Exercise	Weight lifting, Push-ups, Sit-ups
4	Military	Crawling, Kneeling, opening doors
5	Phone usage	Making phone calls, Text messaging
6	Transportation	Riding a bus, Riding a Bike, Driving
7	Upper body	Chewing, Speaking, Sighing, Head Movement

can be used to swiftly examine the amplitude and phase of a signal at any given time. However, this technique lacks relevant signal frequency information.

Frequency-domain features are derived from a signal's frequency fluctuations across time. Over a range of frequencies, the FD method shows how much of a signal stays inside each frequency band [147]. This approach necessitates a lot of computing power, thus it is not ideal for low-power wearable sensors. The wavelet-domain breaks down a signal into a series of fundamental functions called wavelets. It takes discrete-time signals and turns them into discrete wavelet representations [47]. Although signal decomposition into wavelets rather than frequencies yields higher resolution [148], it requires more computer power and takes a long time to find appropriate wavelet energy.

The work of [149], proposed a technique for feature extraction of forearm electromyographic (EMG) signals using a mother wavelet matrix (MWM). Even though hand-crafted features are still viable for HAR due to their low computational complexity and calculation simplicity, using these methods always costs a lot due to the lengthy design and selection of manual features. Other limitations include high reliance on sensor selection and reliance on expert knowledge [50]. Deep neural networks, such as Convolutional Neural Networks (CNN) or Long Short-Term Memory networks (LSTM), have been widely employed for HAR in recent years, completing both feature extraction and activity classification. This method is classified as Automatic Feature Extraction [150].

3.3.2. Automatic feature extraction

In automatic feature extraction, meaningful data representations are automatically discovered from raw data. Research in [50] classified the automatic feature extraction methods from sensor data into three; Codebooks, Principal Component Analysis (PCA), and Deep Learning (Feature Learning). Generally, PCA and codebooks do not learn from data. In codebooks, each sensor data window is treated as a sequence, which then extracts subsequences and groups them into clusters. The centre of each cluster is a codeword. Then, using codewords as features, each sequence is encoded using a bag-of-words technique [151]. In PCA, a set of orthogonal features are extracted, and these features are referred to as principal components [152].

In recent times, deep learning methods have been proposed to extract features directly from time-series data. Due to its properties for an end-to-end pipeline in pattern categorization and learning of fundamental features, deep learning models, notably the convolutional neural network (CNN), are highly appealing in time-series data processing [33,38]. Deep learning models for wearable sensor-based HAR was presented in [38]. This is shown in Table 8.

Deep Learning uses Neural Network engines, and several layers make up a neural network. The input data is transformed in each layer using a combination of filters and topological maps. Each layer's output becomes the input for the next layer, and so on. Depending on the number of layers, the result is an abstract set of features. The more layers there are, the more abstract the features become. These characteristics can be used to classify items. For time series analysis, many deep learning methods for feature extraction have been applied [50].

A lot of researchers have adopted this method for automatic feature learning, as seen in [165,171], among many others. Qian et al. [171] presented a deep learning model for activity recognition that uses a unified framework to automatically extract statistical features, temporal features, and spatial correlation features. Also in [165] an unsupervised deep learning method for feature learning in wearable sensor-based HAR was proposed. The technique worked by extracting crucial features from HAR datasets automatically. To learn the underlying features, the method combines a convolutional denoising autoencoder with a convolutional neural network and provides a compact feature representation of the data. This not only allows for the extraction of more accurate and discriminative features but also lowers the computational cost and enhances the generalization of classification models [164].

3.4. Classification

The rate at which researchers have focused on obtaining accurate and bulky sensor-based HAR datasets has brought about

Table 8
Deep learning models ([38]).

S/N	Model	Description	Research	Datasets
1	DNN	Deep fully-connected network, artificial neural network with deep layers	[153,154]	UCI-HAR, Patient monitoring data,
2	CNN	Convolutional neural network, multiple convolution operations for feature extraction	[75,155–157]	UCI-HAR, WISDM, PAMAP2, OPPORTUNITY, Unimib-SHAR
3	RNN	Recurrent neural network, network with time correlations and Long Short-Term Memory	[158–161]	UCI-HAR, Nursing Activity, WISDM
4	DBN/RBM	Deep belief network and restricted Boltzmann machine	[162,163]	Exercise Activity Dataset, HAPT
5	SAE	Stacked Autoencoder, feature learning by decoding–encoding autoencoder	[164–167]	HAPT, UCI-HAR, WISDM
6	Hybrid	A combination of two or more deep learning models	[168–170]	HAPT,PAMAP2, UCI-HAR, WISDM

the need to recognize patterns, and then use the patterns to train and develop HAR systems. Early research works on HAR systems adopted Machine Learning techniques such as K-Nearest Neighbour [172], Random Forest [173], Support Vector Machine (SVM) [174], and Decision Tree [175] in recognizing activities. This proved to be effective in controlled environments, where few labelled data is required. Generally, researchers at various levels have proposed many models that range from discriminant models, generative models and ensemble models [47].

In recent times, deep learning has achieved unparallelled advancements in various areas such as natural language processing, visual object recognition and logical reasoning [176]. It can be considered as the closest advancement to the next-generation Artificial Intelligence. Recently, the adoption of deep learning for classification has garnered the interest of various researchers. The adoption of deep learning in HAR research as seen in [177–179], among others; was triggered by the relatively low accuracy in recognizing simple low-level activities and the inability to recognize complex activities. For example, in Ascioglu and Senol [180] basic and complex activities were classified. Data was collected by attaching multiple wearable sensors to 60 healthy users (37 males and 23 females). The signals were divided into frames with non-overlapping sliding windows and considered a window size of 1.5 s. The classification was done using CNN, LSTM and ConvLSTM, and experiments showed that ConvLSTM performed better with an accuracy of 94.0%, while CNN and LSTM achieved accuracies of 90.8% and 90.5% respectively. Also, the work of [158], proposed a robust training pipeline that handles sampling rate variability, missing data, and misaligned data time stamps using data augmentation techniques. The model was evaluated on the Cooking Activity Dataset with Macro and Micro Activities using a deep convolutional bidirectional LSTM, and achieved an accuracy of 88% and 72% on macro and micro activities respectively. The performance achieved by these models outperformed classical and ensemble of machine learning techniques. A survey to compare the number of research papers published on activity recognition systems as of 2020 using Machine Learning and Deep Learning was presented in [181]. The result showed that among 146 selected papers, 96 were based on machine learning, and 53 were based on deep learning.

Generally, most conventional pattern recognition techniques focus on learning from static data, while ADL data are dynamic, and they come in streams, requiring robust incremental learning. Illustrations comparing activity recognition based on ML and DL, as seen in [38], are presented in Figs. 5 and 6.

Activity data obtained with wearable sensors are time-series data with high spatial and temporal precision. A pipeline-based approach is used to analyse this data. The first stage is to segment the time series data into contiguous segments, either using a sliding-window segmentation technique or using specific signal characteristics such as signal energy [182]. A set of features are retrieved from each frame, which typically contains statistical information or comes from the frequency domain [183]. As stated earlier, using a collection of features rather than raw data has been shown to enhance classification accuracy. [143].

HAR research is fully reliant on the quantity and quality of data obtained. However, wearable sensor data are sometimes of poor quality and frequently contain missing data. This can occur due to various circumstances, including a person not wearing a sensor correctly or a sensor not working properly [184]. Wearable sensor datasets have been deployed in traditional HAR techniques for recognizing basic and complex human activities, and these techniques have relied on supervised learning; an example of HAR systems developed through supervised learning can be found in [54,73], and [15], among others. Supervised learning necessitates a substantial amount of fully labelled user activity training data which is expensive, time-consuming, difficult to get and impractical for real-world implementation [185]. The amount of labelled data needed in supervised learning is critical to the effectiveness and functionalities of HAR systems but providing enough labelled data is challenging. Also, the quality of wearable sensor data is further affected by intra-class variability, inter-class similarity, class imbalance, and determining the precise start and finish times of each activity [186].

Data collection experiments are generally done with several participants, and the data gathered from various individuals for the same activity set may not be of the same type, resulting in intra-class variance in the data. Furthermore, data from two different activities (such as running and jogging) may be of an equal type, resulting in inter-class variability. A class imbalance may occur when one activity is practised for a longer amount of time than others. For example, a person may stroll for longer than he or she jogs. Because the sensors often have a greater sampling frequency, it is also difficult to pinpoint an activity episode's exact start and finish times [187]. Furthermore, training HAR systems with entirely labelled data prevents them from adapting to changing user actions over time, as fresh activity data must be re-trained [188].

One of the issues synonymous with wearable sensor-based is the problem of insufficient labelled data, which is caused by the expensive and time-consuming cost of collecting labelled data. Datasets obtained through wearable sensors need to be well labelled for activity modelling, and the cost of labelling the large amount of data required for accurate HAR systems is quite

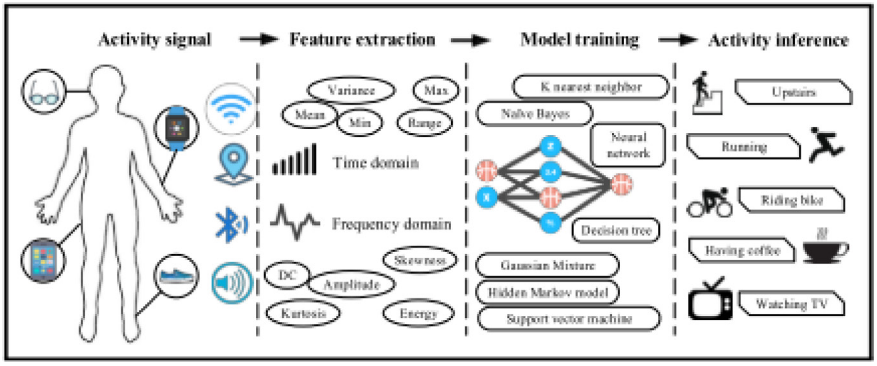

Fig. 5. Illustration of HAR using ML techniques [38].

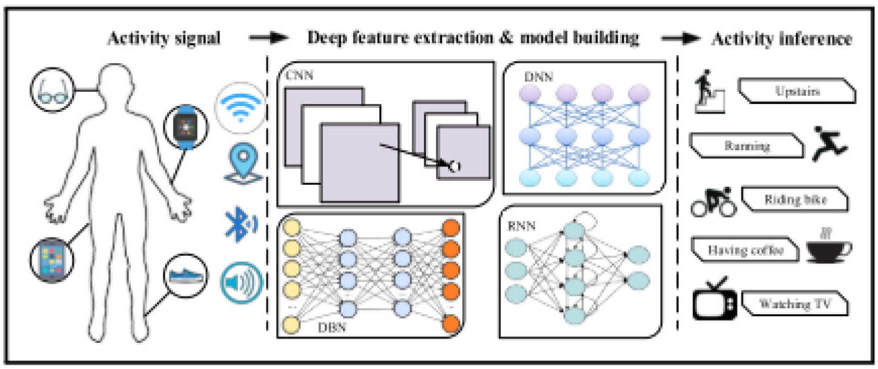

Fig. 6. Illustration of HAR using DL techniques [38].

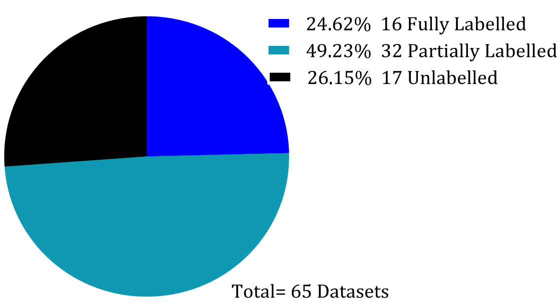

Fig. 7. Illustration of dataset category in CASAS repository.

expensive. For example, on the Center of Advanced Studies in Adaptive System (CASAS) website, a total of sixty-five (65) HAR datasets are available; however, only 15 of the datasets are fully labelled for research. An illustration of this is shown in Fig. 7

Therefore, exploiting unlabelled sensor data to achieve accurate recognition is one of the emerging research areas in HAR. The use of unlabelled sensor-based datasets in HAR systems has shown to be less expensive and time-consuming.

3.5. Exploiting unlabelled data for wearable sensor-based HAR

Training HAR systems with unlabelled wearable sensor datasets work by harnessing related data in order to improve performance and make HAR systems more robust. To achieve this, researchers proposed semi-supervised learning techniques as the solution approach to tackling the challenges of supervised learning. Semi-supervised learning involves combining a small amount of labelled data with a large amount of unlabelled data. For example, in [189], the authors used a wearable sensor dataset with 1% labelled data to develop a general model for activity recognition. The researchers used Latent Dirichlet Allocation (LDA) and AdaBoost to jointly train the model with the partially labelled data. They then used AdaBoost in conjunction with graphical models (HMM and CRF) to exploit the temporal information in human activities to smooth out any inadvertent misclassifications. Experiments on publicly available datasets showed that the model achieved a recognition accuracy of 90%.

Also, in [188], a semi-supervised HAR system was developed, which focused on frequently repeated human activities. To conduct offline human activity recognition on unlabelled data, the framework used a pre-defined short-term system memory and updated the user activity model using Bayesian Networks for real-time detection. The offline and online HARs worked together to continuously learn activity patterns and modify the user activity model on a short-term basis to accommodate any new or changing actions. On the Aruba dataset, the model used Hierarchical Associative Classifier (HAC) to split sensor events into several activity clusters, with an accuracy of 71%. The model was pilot tested and had an F1 score of 0.96. However, the model failed to identify some activities due to an imbalance in the dataset caused by the presence of various unlabelled events that dominated it.

A semi-supervised human activity recognition was also developed in [190], using a dataset obtained through smartphone sensors. The dataset was obtained by placing smartphones in subjects' bags, hips, torso, and hands. The model was developed using Adversarial Autoencoder (AAE) as the base and employed Convolutional Networks for feature extraction. Multiple experiments showed a maximum F1 score of 0.902. Also, in [191], an online semi-supervised HAR system that works together with Bayesian Stream-based Active Learning (BSAL) was developed for smart-home. Conditional Restricted Boltzmann Machine (CRBM) was also deployed to learn features autonomously and extract low-level features from unlabelled raw high-dimensional activity inputs. The developed model was able to recognize various basic activities with high accuracy and also learn new ones.

In Seung et al. [192], semi-supervised active learning that combines semi-supervised learning with existing active learning was proposed. This technique achieved 95.9% performance while also reducing labelling. In Bota et al. [193] a Semi-Supervised Active Learning based on Self-Training for Human Activity Recognition that worked by using criteria to select the most relevant samples for labelling and propagate their label to the most confident samples. The result showed that their method was able to achieve high accuracy, after reducing the number of labelled data used for training by 89%. To tackle challenges associated with partly labelled data, limited deep learning architectures that support semi-supervised learning and sequential dependency, among other limitations of semi-supervised learning; self-supervised learning technique was proposed.

Self-supervised learning entails pre-training a model on a huge quantity of unlabelled data before adjusting it to the target task [39]. Self-supervised learning works by training data D_i, together with its pseudo label P_i, while P_i is automatically generated for a pre-defined pretext task without any human annotation [40]. Recently, research in [98] proposed a method for single sensor-based activity recognition trained from multiple sensors. Although, these developments have improved state-of-the-arts in HAR research; however, the number of fully labelled sensor-based datasets available to train and develop HAR systems is still minimal.

For example, [194], developed a multi-task self-supervised learning model for HAR by using Transformation Prediction Network (TPN) as a multi-branch temporal convolutional neural network with a common trunk (shared layers) and a distinct head (private layers) for each task with a separate loss function. Precision, recall, F1-score and kappa score were considered as performance metrics, and evaluation was done on six publicly available wearable sensor datasets (HHAR, MobiAct, MotionSense, WISDM, UCI HAR, and UniMiB). The results showed that the model performed better than supervised and semi-supervised methods.

Also, researchers have proposed contrastive learning. Contrastive learning models work by learning to extract representations by contrasting positive pairs, i.e. samples deemed to be similar against negative pairs. An example is in [195], where the authors adopted SimCLR, a contrastive learning technique commonly used in visual representation. In order to adopt SimCLR for wearable sensors, the authors modified by adding random Gaussian noise, randomly scrambling sections of signals, and reversing the direction of time; among other modifications. A lightweight neural network architecture, Transformation Prediction Network (TPN), which was proposed in [194] was used as the base encoder, a three-layer fully connected MultiLayer Perceptron was used as the projection head, and the result showed a better performance of 0.942 F1 score when compared to the supervised approach which recorded an F1 score of 0.922.

Even though self-supervised learning has achieved better performance in human activity recognition when compared to others, it is only concerned about drawing conclusions from classification and regression. The desire to develop state-of-the-arts wearable sensor-based HAR systems using fully unlabelled data has motivated researchers to develop HAR systems through unsupervised learning techniques. The first attempt to propose unsupervised learning for wearable sensor-based HAR systems was in [196]. This has since changed the way researchers have approached developing state-of-the-arts wearable sensor-based HAR systems.

4. Unsupervised learning in wearable sensor-based HAR

Unsupervised learning is mainly used for exploratory data analysis in order to find patterns in data [37], and recent advancements have seen its applicability in wearable sensor-based HAR. An example of an unsupervised learning technique in wearable sensor-based HAR is in [197], where the authors developed an unsupervised sensor-based HAR system using unlabelled data obtained through wearable sensors. The researchers focused on accurately classifying fully unlabelled wearable sensor data using the K-means clustering technique and built the model using Autoencoders. The Autoencoder is an unsupervised learning framework for finding efficient data encodings. It encodes crucial input properties into a hidden representation and then reconstructs the inputs using the hidden representations. It is used for dimension reduction, pre-training of deep hierarchical models, and other things. The research tested a varying number of clusters on publicly available datasets and obtained impressive accuracy. However, locality preserving loss caused some closely related activities to be located closely in the embedding space. Another approach is the Deep belief Network (DBNs), which comprises multiple layers of hidden units [198].

Research has shown that unsupervised techniques have addressed some of the challenges of supervised, semi-supervised and self-supervised learning in HAR, especially in the area of the insufficient labelled training dataset. However, wearable sensor data quality is often poor, and missing data is common. This can happen for various reasons, including an individual not properly wearing a sensor or a malfunctioning sensor [184]. Similarly, sensor data may be very unbalanced due to large individual variations, with limited labels for some activities [187]. Because of these limitations, recent research has focused on training HAR models with a larger number of unlabelled wearable sensor data without incurring more data collection costs. To achieve this, some data augmentation methods have been proposed. However, issues relating to temporal coherence, class imbalance, and quality data clustering still linger, as unsupervised learning relies heavily on quality clustering. These existing challenges have motivated recent research in unsupervised wearable sensor-based human activity recognition. The existing state-of-the-arts adopted in addressing these challenges are presented in the next sub-sections.

4.1. Clustering in wearable sensor-based HAR

The purpose of clustering is to identify structure in unlabelled data by objectively grouping data into homogeneous groups, with the least within-group object similarity and the highest between-group object dissimilarity [199]. As shown in Fig. 8, clustering stages involves the feature selection stage, clustering method selection stage, validation stage, and cluster result interpretation stage.

Clustering can be done through Partitional method [36], hierarchical method [200], diffuse method [201], methods based on neural networks [202], evolutionary method [203], kernel-based method [204], and spectral methods [205]. In the partitional method, a single data partition is considered without the need for a second sub-partition. The separation of groups in the form of hypersurfaces is the outcome of this method. The fundamental accomplishment of partition algorithms is to evaluate the distances between the processed items, which has a broad range of applications in addressing various issues. Examples of this method include the K-means algorithm [206], K-medoids [207], CLARA, and CLARANS [208]. However, limitations such as weak cluster descriptors and high sensitivity to the initialization phase, noise, and outliers are attributed to this method.

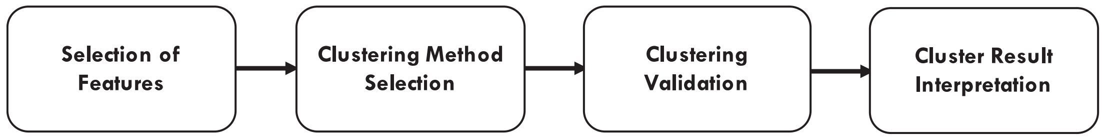

Fig. 8. Clustering stages.

Hierarchical methods [200] is designed to improve a specific function. Objects in the same cluster should be similar, whereas those in other groupings should be as dissimilar as feasible. The key differences between the numerous algorithms used in this method are the measure of similarity and the criteria used to assess the overall quality of the grouping. Examples include BIRCH [209], ROCK [210], and others. The limitation of this method is the number of clusters that must be preset which makes it relatively time-consuming. The diffuse method [201] identifies the many classes that represent the various functional states that exist in a system while considering the historical dataset available. Expert personnel are required to determine the degree of relationship of the selected classes. An example of this is the Fuzzy C Means. The limitation of this method is that the clustering result is susceptible to the initial parameters, and it has limited scalability. Neural Networks methods [202] provides a more efficient and secure way to cluster large amounts of data. A typical example of this is the Self Organizing Maps [211]. The limitation of this method is that it requires adequate neuron weights to cluster input.

In Evolutionary methods [203], Heuristic objectives are used, which are then used to analyse the evolutionary process using different types of computational models. Example of this is the Genetic algorithms [212]. However, this method does not scale well with increasing complexity. In the Kernel-based method [204], a weighted graph is built for the initial dataset, with each node representing a pattern and each weighted edge changing the values based on that pattern. An example is the Kernel K-means [213], which has significant temporal complexity. Lastly, compared to previous algorithms, spectral methods [205] are one of the most current methods of executing clustering operations; they are simple to implement and can efficiently handle problems under linear algebraic criteria with extremely excellent performance.

In order to cluster time series data, the most used method is to compute a similarity measure between different time series and then use that value to produce either spherical cluster divisions or non-spherical cluster partitions. Another common technique is to extract features from time series and then use those traits to cluster the data, either using a multinomial distribution (where the number of clusters is known ahead of time) or a Dirichlet Process (where the number of clusters is not known apriori). Some existing similarity metrics that are used to determine how similar or dissimilar distinct sensor-based time-series data are: Autocorrelation based distances, Normalized Compression Distance (NCD), Periodogram-based distances (PER), Euclidean Distance (EUCL), Compression-based dissimilarity measure, Dynamic Time Warping (DTW) measure, Discrete Wavelet Transform (DWT) measure, Correlation-based dissimilarity (COR), Autocorrelation based dissimilarity (PACF), Complexity Invariant Distance (CID) measure, Permutation Distribution Clustering (PDC), among others. Sensor-based data can be clustered using three main approaches; raw-data based, feature-based and model-based, as shown in Fig. 9. The use of a reduced extracted feature set has also been shown to increase the performance of clustering algorithms. For example, Dobbins & Rawassizadeh [214], used PCA Feature Selection and CFS to reduce extracted features by removing redundant features. The features were then clustered using HCA, K-means and DBSCAN. By doing this, the accuracy of the resulting clusters increased when compared to the baseline.

Generally, unsupervised learning is heavily dependent on effective clustering. Examples can be seen in some unsupervised wearable sensor-based HAR models such as Trabelsi et al. [215], Kwon et al. [216], and also in Sheng and Huber [197], among many others that are later discussed. A summary of some existing activity recognition models based on clustering is shown in Table 9.

As shown in Table 9, varying clustering performance have been achieved by the existing clustering models. This is because some models were evaluated on datasets that contains more activities, and also some factors associated with the method of feature representation and extraction. To give more insight into some of these factors, the existing works are later discussed in details, together with their error sources.

In Trabelsi et al. [215], their model was based on employing a Hidden Markov Model (HMM) in a multiple regression context to jointly segment multidimensional time-series data. The model was learned using the Expectation-Maximization (EM) algorithm which is based on a Hidden Markov Model (HMM) in a multiple regression context in an unsupervised setting with no activity labels. The model took into account the data's order of appearance, and the most likely sequence of activities is then estimated using the Viterbi algorithm. The model was modified to detect actions accurately using temporal acceleration data. The results, when tested against a supervised approach, showed improved performance. However, the number of clusters in the data was pre-determined, which is not feasible when dealing with a large sensor-based HAR dataset. Kwon et al. [216], developed an unsupervised model with no pre-determined number of clusters and compared three clustering algorithms independently; K-means, Mixture of Gaussian (GMM), Average-Linkage Hierarchical Agglomerative Clustering (HIER), and DBSCAN. Experiments showed that the K-means algorithm, GMM and HEIR showed a relatively lower accuracy as the number of activities considered increased, while DBSCAN achieved an accuracy of over 90%. However, issues of low accuracy when the number of activities was increased together with locality preserving loss were not addressed. Kafle & Duo [217], proposed a heterogeneous clustering technique. To avoid the problem of pre-specifying the number of clusters in the dataset, the model performed clustering using a Bayesian semi-parametric technique. The method uses the number of clusters in the sensor-based HAR dataset as a model parameter. Experiments showed that the model achieved an accuracy of 35%, which performed better than some existing time series clustering techniques. However, the model could only classify the dataset into five clusters, the quantity of unlabelled data used was few, and the clustering accuracy was relatively low. Also, the clusters were not deployed in the training of a human activity recognition system.

Mejia-Ricart et al. [220], compared the efficiency of k-means, spectral clustering, hierarchical clustering (Ward's Method and Average Linking), DBSCAN and mean shift. The clustered unlabelled dataset was compared to the labelled data, and the result showed that DBSCAN and Mean Shift failed at clustering the unlabelled data, as DBSCAN was overly stringent, ignoring many sample windows as noise and failed to produce a significant cluster. Clusters similar enough to be evaluated were also not found using Average Linking or Mean Shift. However, Spectra C, Ward's

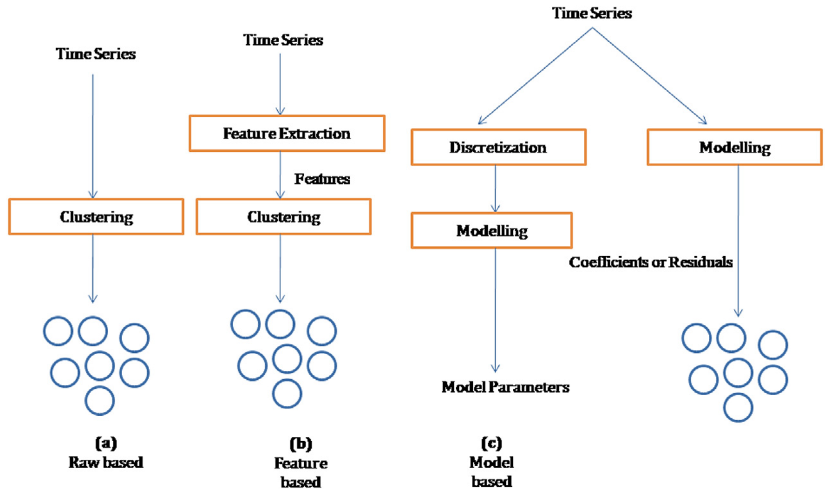

Fig. 9. Sensor-based dataset clustering approach [199].

Table 9
Clustering in Wearable Sensor-based HAR.

Authors	Clustering method	No. of Activities	Results			
			Accuracy	NMI	Precision	F1 Score
Trabelsi et al. [215]	MHMMR	12	–	–	89%	–
Kwon et al. [216]	K-Means, GMM, HEIR	5	71.98%, 90%, 79.98%	86.70%, 100%, 90.92%	–	–
Kafle & Duo [217]	Hierarchical Heterogeneity	5	35%	–	–	–
Ma et al. [218]	CNN-BiLSTM Autoencoder and K-means	6, 6, 11	–		72.50%	70.70%
Qi et al. [3]	Hierarchical K-medoids	5	96.55%	–	–	89.77%
He et al. [219]	Wavelet Packet Transform and Half-cosine Fuzzy Clustering	6	88.5%	–	–	–
Mejia-Ricart et al. [220]						
Jun & Choi [221]	Autoencoder & K-means	4	96.0%		98.0%	95.0%
Sheng & Huber [197]	Domain-Specific Autoencoder & K-means	12, 33, 6	92.11%, 71.49%, 80.73%	91.44%, 82.82%, 79.82%	–	–
Bai et al. [222]	Bi-LSTM Autoencoder	9	87%	–	–	–
Abedin et al. [223]	Multi-Task Autoencoder & Deep Sensory Clustering	6, 10, 12	75.41%, 53.48%, 56.85%	71.25%, 59.06%, 63.06%	–	–
Konak et al. [224]	K-means, DBSCAN, IIC	4	40.8%, 36.0%	–	–	

method and K-Means were able to cluster the dataset, with K-Means outperforming the other clustering algorithms. Abedin et al. [223], proposed a deep sensory clustering model using raw sensor data. The model used a recurrent multi-task autoencoder to extract representations from sensor sequences. A 2-layer bi-directional GRU with 256 hidden units was used in the encoder, while the decoder used uni-directional connections. Clustering assignment hardening was adopted for feature space refinement, and the model was tested on three benchmarking datasets. Results showed a better clustering accuracy when compared to traditional clustering techniques. Ma et al. [218] proposed an end-to-end multi-task deep clustering framework. The researchers used a CNN-BiLSTM autoencoder to create a compressed latent feature representation using unlabelled multi-dimensional sensing data as input. The dataset was then partitioned into separate groups using a K-means clustering technique based on the retrieved features, which produced pseudo labels for the instances. These were then fed to Deep Neural Network to train the classifier for HAR. Experiments on three publicly available datasets at various conditions showed that the model performed better than existing supervised techniques. However, the clustering quality was at 0.55 after 400 iterations, and the issue of temporal differences in the clustered dataset was not addressed.

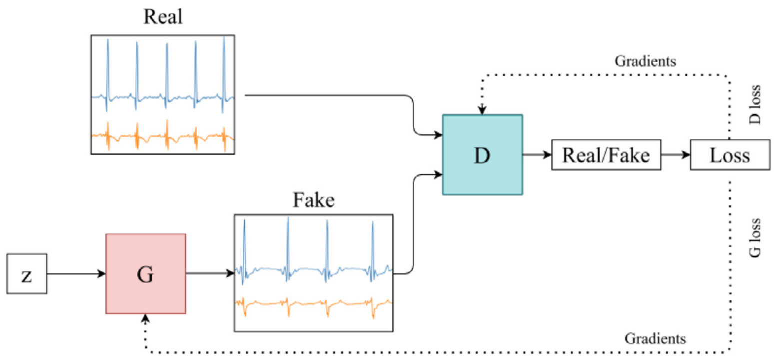

Fig. 10. Generative Adversarial Networks.

Literature has shown that the more dataset used in training a HAR model, the higher the chances of improving recognition accuracy and that the adoption of unsupervised learning in wearable sensor-based HAR has proffer solutions to the challenges of labelling wearable sensor data. However, issues such as insufficient unlabelled data, imbalanced data, and temporal coherence leading to inaccurate clustering, among other challenges, are still associated with unsupervised learning in wearable sensor-based activity recognition. These constraints often lead to poor predictive performance and a lack of model generalization. Using data augmentation techniques to extend the data is one approach to address this issue. For this reason, researchers have been motivated to propose sensor-data augmentation methods (synthetic data generation) to obtain more wearable sensor-based datasets without incurring additional costs.

4.2. Data augmentation in wearable sensor-based HAR

According to general studies, data augmentation (synthetic data generation) can be done using Autoencoders and Generative Adversarial Networks (GANs). Autoencoders learn the informative representation of an input in a small dimensional space and recover the encoded data as closely as feasible to the original. They are made up of an encoder and decoder neural network. However, they are not adopted in time series data generation because synthetic data generated by AE tends to be of less quality, while GANs are capable of generating high-quality synthetic time series data [225].

Generative Adversarial Networks was first presented in Goodfellow [226]. GANs function by establishing a competition between a generator and a discriminator, as shown in Fig. 10. The generator creates samples that are expected to be verisimilar to the training data. The discriminator inspects samples to determine if they are genuine or not. The generator aims to generate verisimilar data until the discriminator is convinced that the generated data belongs to the same distribution as the training data. Early adoption of GAN was in the generation of quality images, and the success garnered with this has led to its adoption in other domains such as speech enhancement [227] and language generation [228], among other domains. The general objective function of GAN where G is the generator, D is the discriminator, z is an apriori distribution noise, $pz(z)$ is fake data distribution, and $pdata(x)$ is real data distribution.

$$\min_{G}\max_{D} \mathbb{E}_{x\sim pdata(x)}\left[\log\left(D\left(x\right)\right)\right] + \mathbb{E}_{z\sim pz(z)}\left[\log(1 - D\left(G(z)\right))\right]$$

The first adoption of GANs in sensor-based HAR can be seen in [229], where a variant of GAN called SensoryGANs was proposed. The recent adoption of GANs in wearable sensor-based HAR has seen several variants of GANs proposed in generating synthetic time series data. However, some limitations, such as non-convergence and mode collapse, are attributed to the GAN architecture. Non-convergence occurs when the model does not stabilize and continuously oscillates, causing it to diverge. Also, mode collapse occurs when the generator collapses, thereby producing only uniform samples with little to no variety. These limitations have motivated various researchers to propose several variants of GANs for wearable sensor-based HAR. An example is in [230], where a variant of GANs is called an Infinite Gaussian Mixture Model Generative Adversarial Networks (IGGM-GAN). This model was developed to address issues related to the anomaly in Human Activity datasets. The researcher stated the limitation of other GANs architecture is based on their poor performance in handling multimodal patterns.

The IGGM-GAN as shown in Fig. 11, which is an improvement on the Bi-GAN model in [231] includes an encoder (E) that learns the inverse of the generator. While the generator learns the mapping from the latent dimension to data, the encoder will then learn a mapping from data to the latent dimension. In [232], an adaptive training ratio strategy was proposed to improve the convergence rapidity and stability of an Enhanced Generative Adversarial Network (EGAN) training process. Results confirm the superior performance of the EGAN when tested with two datasets. While most GANs are based on Long Short-Term Memory (LSTM), research in [233] presented a unified architecture of GAN named ActivityGAN, that can effectively generate time-series sensor data of human activities. This GAN variant employed 1D-CNN, 1D-transposed CNN, and a 2D-CNN to generate sensor data of human activities without using LSTM or Recurrent Neural Networks (RNN).

Literature has shown that several variants of GANs focus on addressing a particular limitation of other GANs, limitations such as; mode collapse, convergence issues, issues caused by base deep learning architecture and limitations caused by training stability. In [234], a deep learning-based architecture was presented to generate a synthetic wearable sensory dataset. The model comprises a generator that is a stack of various Long–Short-Term-Memory (LSTM) networks and Mixture Density Network (MDN), an LSTM network that functions as a discriminator model to distinguish between real and synthetic sensor datasets. The model was trained using a dataset of accelerometer traces obtained through smartphones, and the evaluation result showed that the model was able to distinguish between real and synthetic data with an accuracy of 50%. Although this model is similar to Generative Adversarial Network, adversarial training was not considered, and the output of the discriminator was not used to train the generator. Also, the researchers did not consider developing a HAR model with the generated synthetic data.

Also in [235], a Wasserstein Generative Adversarial Network (WGAN)-based approach for HAR was used to automatically synthesize basic and complex unlabelled sensor data. The synthetic data was assessed using Convolutional Neural Network (CNN)

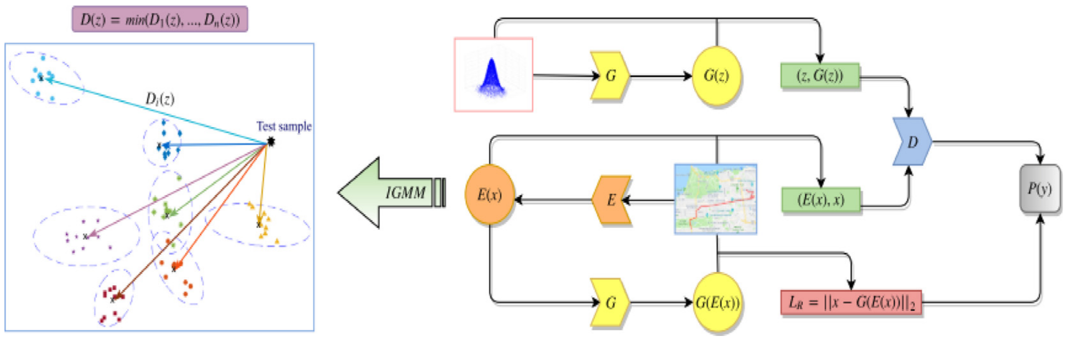

Fig. 11. The IGGM-GAN architecture [230].

and Long Short-Term Memory (LSTM). The model was tested on publicly available datasets, and the performance of using WGAN augmented training data over imbalanced data was evaluated. An F1 score of 0.85 was recorded in imbalanced data and 0.95 in WGAN generated synthetic data in the first dataset. For the second dataset, a 0.70 F1 score was recorded on imbalanced data, while the WGAN generated data had an F1 score of 0.77 when CNN activity classifier was used. In [236], a unified generative model was developed to generate verisimilar data of five basic activities. The model was capable of generating data with similar patterns and also data with diverse characteristics. The authors generated synthetic data for walking, jogging, lying down, cycling, and standing. The model was able to learn many activity classes of sensor data simultaneously without experiencing mode collapse, and it achieved a classification accuracy of 85%.

5. Future direction

The adoption of unsupervised learning in wearable sensor-based HAR has been presented, and the cogent aspect of the wearable sensor-based HAR process has been reviewed. For future research, some grand areas where wearable sensor-based HAR researchers can focus are presented as follows:

i. Complex high-level activity dataset: The existing wearable sensor datasets are generally focused on activities of daily living, kitchen activities, and exercise, among others. Datasets with more complex activities can be proposed.

ii. Clustering: Data clustering is the most critical aspect of unsupervised learning. Even though recent researchers are proposing multi-task deep clustering approaches, they have not been able to fully address temporal coherence and feature space locality limitations, which are associated with wearable sensor-based datasets. Future work can investigate the performance of the ensemble of some clustering methods in addressing these issues for unsupervised wearable sensor-based HAR.

iii. Synthetic data generation for complex activities: The concept of generating synthetic data has been discussed in this survey; however, existing models have not been able to generate quality synthetic complex and transitional activity data. Also, the generated synthetic signals are of fixed length while some activities especially the transitional activities have different time completion. Moreover, activities are carried out in a continuous manner such as from walking to standing followed by sitting. Thus, designing a generative model with attention decoder could continuously generate signals with varying lengths. This area is still open to extensive research.

iv. Complex future activity prediction: The concept of using complex wearable sensor-based HAR datasets to predict future activities to be performed by a subject has not yet been explored. This can be valuable in various domains such as sports (boxing, lawn tennis) and many other areas.

6. Conclusion

This survey discusses the adoption of unsupervised learning in wearable sensor-based activity recognition. Each process of wearable sensor-based activity recognition has been discussed with regard to the evolution of sensor-based HAR, manual and automatic feature extraction methods, data segmentation methods and the existing classification methods employed in achieving state-of-the-art. We collate thirty-three wearable sensor-based HAR datasets that researchers can use to evaluate their models and also presented the properties, activity class and the number of research papers that have benchmarked their models on each dataset. Furthermore, the state-of-the-art approaches in unsupervised learning of wearable sensor-based activity recognition were also discussed, and we reviewed various clustering methods and the existing methods adopted in addressing imbalanced dataset issues, temporal coherence issues, and class imbalance through data augmentation, and the state-of-the-art in achieving this was also presented. Finally, we presented some future research areas which wearable sensor-based activity recognition researchers can explore. By doing this, we have been able to contribute to the gap of unavailability of survey papers addressing these areas. The information in this survey will serve as background literature and effectively aid researchers on the issues to address in order to develop next-generation state-of-the-art activity recognition models.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

References

[1] A. Ferrari, D. Micucci, M. Mobilio, P. Napoletano, On the personalization of classification models for human activity recognition, IEEE Access 8 (2020) 32066–32079, http://dx.doi.org/10.1109/ACCESS.2020.2973425.
[2] Ó.D. Lara, M.A. Labrador, A survey on human activity recognition using wearable sensors, IEEE Commun. Surv. Tutor. 15 (3) (2013) 1192–1209, http://dx.doi.org/10.1109/SURV.2012.110112.00192.
[3] W. Qi, et al., Depth vision guided human activity recognition in surgical procedure using wearable multisensor, in: 2020 5th International Conference on Advanced Robotics and Mechatronics, 2020, pp. 431–436.
[4] J. Ben-Arie, Z. Wang, P. Pandit, S. Rajaram, Human activity recognition using multidimensional indexing, IEEE Trans. Pattern Anal. Mach. Intell. 24 (8) (2002) 1091–1104.
[5] H.C. Tan, L.C. De Silva, Human activity recognition by head movement using Elman network and Neuro-Markovian hybrids, in: Proc. of Image and Vision Computing New Zealand, 2003, pp. 320–326.

[6] E. Ramasso, C. Panagiotakis, M. Rombaut, D. Pellerin, G. Tziritas, Human shape-motion analysis in athletics videos for coarse to fine action/activity recognition using transferable BeliefModel, in: ELCVIA: Electronic Letters on Computer Vision and Image Analysis, 2008, pp. 32–50.

[7] L. Chen, J. Hoey, C.D. Nugent, D.J. Cook, Z. Yu, Sensor-based activity recognition, IEEE Trans. Syst. Man Cybern. C 42 (6) (2012) 790–808, http://dx.doi.org/10.1109/TSMCC.2012.2198883.

[8] M. Zhang, A.A. Sawchuk, USc-HAD: A daily activity dataset for ubiquitous activity recognition using wearable sensors, in: UbiComp12 - Proc. 2012 ACM Conf. Ubiquitous Comput, 2012, pp. 1036–1043.

[9] J.R. Kwapisz, G.M. Weiss, S.A. Moore, Activity recognition using cell phone accelerometers, SIGKDD Explor Newsl. 12 (2) (2011) 74–82, http://dx.doi.org/10.1145/1964897.1964918.

[10] Q. Zhu, Z. Chen, Y.C. Soh, A novel semisupervised deep learning method for human activity recognition, IEEE Trans. Ind. Inf. 15 (7) (2019) 3821–3830, http://dx.doi.org/10.1109/TII.2018.2889315.

[11] J.A. Ward, P. Lukowicz, G. Troster, T.E. Starner, Activity recognition of assembly tasks using body-worn microphones and accelerometers, IEEE Trans. Pattern Anal. Mach. Intell. 28 (10) (2006) 2006.

[12] T. Van Kasteren, A. Noulas, G. Englebienne, B. Kröse, Accurate activity recognition in a home setting, in: UbiComp 2008 - Proc. 10th Int. Conf. Ubiquitous Comput, 2008, pp. 1–9, http://dx.doi.org/10.1145/1409635.1409637.

[13] J.T. Sunny, S.M. George, J.J. Kizhakkethottam, Applications and challenges of human activity recognition using sensors in a smart environment, IJIRST –Int. J. Innov. Res. Sci. Technol. 2 (04) (2015) 50–57.

[14] F. Palumbo, C. Gallicchio, R. Pucci, A. Micheli, Human activity recognition using multisensor data fusion based on reservoir computing, J. Ambient Intell. Smart Environ. 8 (2) (2016) 87–107, http://dx.doi.org/10.3233/AIS-160372.

[15] L. Liu, Y. Peng, M. Liu, Z. Huang, Sensor-based human activity recognition system with a multilayered model using time series shapelets, Knowl.-Based Syst. 90 (2015) 138–152, http://dx.doi.org/10.1016/j.knosys.2015.09.024.

[16] C. Chen, R. Jafari, N. Kehtarnavaz, UTD-MHAD: A multimodal dataset for human action recognition utilizing a depth camera and a wearable inertial sensor, in: Proc. - Int. Conf. Image Process. ICIP, 2015-Decem, 2015, pp. 168–172, http://dx.doi.org/10.1109/ICIP.2015.7350781.

[17] T. Choudhury, S. Consolvo, B. Harrison, The mobile sensing platform: An embedded activity recognition system, IEEE Pervasive Comput. 7 (2) (2008) 32–41.

[18] S. Bhattacharya, P. Nurmi, N. Hammerla, T. Plötz, Using unlabeled data in a sparse-coding framework for human activity recognition, Pervasive Mob. Comput. 15 (2014) 242–262.

[19] M. Stikic, B. Schiele, Activity recognition from sparsely labeled data using multi-instance learning, Proc. Locat. Context Aware. 5561 (2009) 156–173.

[20] S. Khalifa, M. Hassan, A. Seneviratne, Pervasive self-powered human activity recognition without the accelerometer, in: IEEE International Conference on Pervasive Computing and Communications (PerCom), 2015, pp. 79–86.

[21] L. Chen, C.D. Nugent, Ontology-based activity ecognition in intelligent pervasive environments, Int. J. Web. Inf. Syst. 5 (4) (2009) 410–430.

[22] M.G. Rasul, M.H. Khan, L.N. Lota, Nurse care activity recognition based on convolution neural network for accelerometer data, in: UbiComp/ISWC 2020 Adjunct - Proceedings of the 2020 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2020 ACM International Symposium on Wearable Computers, 2020, pp. 425–430, http://dx.doi.org/10.1145/3410530.3414335.

[23] S.R. Taghanaki, A. Etemad, Self-supervised wearable-based activity recognition by learning to forecast motion, 2020, arXiv.

[24] H. Alemdar, C. Ersoy, Wireless sensor networks for healthcare: A survey, Comput. Netw. 54 (15) (2010) 2688–2710.

[25] M. Babiker, O.O. Khalifa, K.K. Htike, A. Hassan, M. Zaharadeen, Automated daily human activity recognition for video surveillance using neural network, in: IEEE 4th International Conference on Smart Instrumentation, Measurement and Application (ICSIMA), 2017, pp. 1–5.

[26] W. Lin, M.T. Sun, R. Poovandran, Z. Zhang, Human activity recognition for video surveillance, in: IEEE International Symposium on Circuits and Systems, 2008, pp. 2737–2740.

[27] E. De Maria, T. L'Yvonnet, S. Moisan, J.P. Rigault, Probabilistic activity recognition for serious games with applications in medicine, in: Communications in Computer and Information Science, Vol. 1165, CCIS, 2020, pp. 106–124, http://dx.doi.org/10.1007/978-3-030-46902-3_7.

[28] S. Khare, S. Sarkar, M. Totaro, Comparison of sensor-based datasets for human activity recognition in wearable IoT, in: IEEE World Forum Internet Things WF-IoT 2020 - Symp. Proc, 2020, pp. 1–6, http://dx.doi.org/10.1109/WF-IoT48130.2020.9221408.

[29] C. Wang, A.C.D.C. Williams, N.D. Lane, N. Bianchi-berthouze, Leveraging activity recognition to enable protective behavior detection in continuous data, Proc. ACM Interact. Mob. Wearable Ubiquitous Technol. 5 (2) (2021) 1–24.

[30] J. Liu, Convolutional neural network-based human movement recognition algorithm in sports analysis, Front. Psychol. 12 (2021) 1738.

[31] J. Manjarres, P. Narvaez, K. Gasser, W. Percybrooks, M. Pardo, Physical workload tracking using human activity recognition with wearable devices, Sensors 20 (1) (2020) 39.

[32] G. Paragliola, A. Coronato, Gait anomaly detection of subjects with parkinson's disease using a deep time series-based approach, IEEE Access 6 (2018) 73280–73292.

[33] M.H.M. Noor, A. Nazir, M.N.A. Wahab, J.O.Y. Ling, Detection of freezing of gait using unsupervised convolutional denoising autoencoder, IEEE Access 9 (2021) 115700–115709, http://dx.doi.org/10.1109/ACCESS.2021.3104975.

[34] C.Y. Ma, M.H. Chen, Z. Kira, G. AlRegib, TS-LSTM and temporal-inception: Exploiting spatiotemporal dynamics for activity recognition, Signal Process., Image Commun. 71 (2019) 76–87, http://dx.doi.org/10.1016/j.image.2018.09.003.

[35] J. Ye, G. Stevenson, S. Dobson, A top-level ontology for smart environments, Pervasive Mob. Comput. 7 (2011) 359–378.

[36] P.A. Colpas, E. Vicario, E. De-La-Hoz-Franco, M. Pineres-Melo, A. Oviedo-Carrascal, F. Patara, Unsupervised human activity recognition using the clustering approach: A review, Sens. Switz. 20 (9) (2020) http://dx.doi.org/10.3390/s20092702.

[37] K. Chen, D. Zhang, L. Yao, B. Guo, Z. Yu, Y. Liu, Deep learning for sensor-based human activity recognition, ACM Comput. Surv. 54 (4) (2021) 1–40, http://dx.doi.org/10.1145/3447744.

[38] J. Wang, Y. Chen, S. Hao, X. Peng, L. Hu, Deep learning for sensor-based activity recognition: A survey, Pattern Recognit. Lett. 119 (2019) 3–11, http://dx.doi.org/10.1016/j.patrec.2018.02.010.

[39] H.H. Mao, A survey on self-supervised pre-training for sequential transfer learning in neural networks, 2020, pp. 1–25, ArXiv200700800v1 CsLG 1 2020.

[40] L. Jing, Y. Tian, Self-supervised visual feature learning with deep neural networks: A survey, IEEE Trans. Pattern Anal. Mach. Intell. (2020) 1, http://dx.doi.org/10.1109/tpami.2020.2992393.

[41] A. Patel, J. Shah, Sensor-based activity recognition in the context of ambient assisted living systems: A review, J. Ambient Intell. Smart Environ. 11 (4) (2019) 301–322, http://dx.doi.org/10.3233/AIS-190529.

[42] H.F. Nweke, Y.W. Teh, M.A. Al-garadi, U.R. Alo, Deep learning algorithms for human activity recognition using mobile and wearable sensor networks: State of the art and research challenges, Expert Syst. Appl. 105 (2018) 233–261, http://dx.doi.org/10.1016/j.eswa.2018.03.056.

[43] E. De-La-Hoz-Franco, P. Ariza-Colpas, J.M. Quero, M. Espinilla, Sensor-based datasets for human activity recognition - A systematic review of literature, IEEE Access 6 (c) (2018) 59192–59210, http://dx.doi.org/10.1109/ACCESS.2018.2873502.

[44] A. Prati, C. Shan, K.I. Wang, Sensors, vision and networks : From video surveillance to activity recognition and health monitoring, J. Ambient Intell. Smart Environ. 11 (2019) 5–22, http://dx.doi.org/10.3233/AIS-180510.

[45] Z. Hussain, M. Sheng, W.E. Zhang, Different approaches for human activity recognition- A survey, 2019, pp. 1–28, arXiv.

[46] M. Suresha, S. Kuppa, D.S. Raghukumar, A study on deep learning spatiotemporal models and feature extraction techniques for video understanding, Int. J. Multimed. Inf. Retr. 9 (2) (2020) 81–101, http://dx.doi.org/10.1007/s13735-019-00190.

[47] L. Minh Dang, K. Min, H. Wang, M. Jalil Piran, C. Hee Lee, H. Moon, Sensor-based and vision-based human activity recognition: A comprehensive survey, Pattern Recognit. 108 (2020) http://dx.doi.org/10.1016/j.patcog.2020.107561.

[48] P. Kumar, S. Chauhan, Human activity recognition with deep learning : Overview, challenges & possibilities, in: CCF Transactions on Pervasive Computing and Interaction, (February) 2021, pp. 1–21, http://dx.doi.org/10.20944/preprints202102.0349.v1.

[49] R. Liu, A.A. Ramli, H. Zhang, E. Henricson, X. Liu, An overview of human activity recognition using wearable sensors: Healthcare and artificial intelligence, 2021, pp. 1–14, ArXiv210315990v3 CsHC.

[50] A. Ferrari, D. Micucci, M. Mobilio, P. Napoletano, Trends in human activity recognition using smartphones, J. Reliab. Intell. Environ. 7 (3) (2021) 189–213, http://dx.doi.org/10.1007/s40860-021-00147-0.

[51] O.X. Schlmilch, B. Witzschel, M. Cantor, E. Kahl, R. Mehmke, C. Runge, Detection of posture and motion by accelerometry: a validation study in ambulatory monitoring, Comput. Hum. Behav. 15 (5) (1999) 571–583.

[52] N.H. Goddard, M. Shah, R. Jain, Human activity recognition, motion based recognit, in: Comput. Imaging Vis. - Springer, Vol. 9, 1997, http://dx.doi.org/10.1007/978-94-015-8935-2_7.

[53] L. Bao, S.S. Intille, Activity recognition from user-annotated acceleration data, in: Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), Vol. 3001, 2004, pp. 1–17, http://dx.doi.org/10.1007/978-3-540-24646-6_1.
[54] C. Pham, P. Olivier, Slice & Dice: Recognizing food preparation activities using embedded accelerometers, in: Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), Vol. 5859, LNCS, 2009, pp. 34–43, http://dx.doi.org/10.1007/978-3-642-05408-2_4.
[55] G.A. Sigurdsson, G. Varol, X. Wang, A. Farhadi, I. Laptev, A. Gupta, Hollywood in homes: Crowdsourcing data collection for activity understanding, in: Lecture Notes in Computer Science, Vol. 9905, in: LNCS, 2016, pp. 510–526, http://dx.doi.org/10.1007/978-3-319-46448-0_31.
[56] Z. Boraston, S.J. Blakemore, The application of eye-tracking technology in the study of autism, J. Physiol. 581 (3) (2007) 893–898, http://dx.doi.org/10.1113/jphysiol.2007.133587.
[57] L. Ball, et al., Eye-gaze access to AAC technology for people with amyotrophic lateral scelerosis, J. Med. Speech - Lang. Pathol. 18 (3) (2010) 11–23.
[58] S.R. Ke, H.L.U. Thuc, Y.J. Lee, J.N. Hwang, J.H. Yoo, K.H. Choi, A review on video-based human activity recognition, 2, (2) (2013). http://dx.doi.org/10.3390/computers2020088.
[59] H.B. Zhang, et al., A comprehensive survey of vision-based human action recognition methods, Sensors (Switzerland) 19 (5) (2019) 1–20, http://dx.doi.org/10.3390/s19051005.
[60] R. Poppe, A survey on vision-based human action recognition, Image Vis. Comput. 28 (6) (2010) 976–990.
[61] M. Philipose, Large-scale human activity recognition using ultra-dense sensing, Bridge Natl. Acad. Eng. 35 (4) (2005).
[62] D.H. Wilson, C. Atkeson, Simultaneous tracking and activity recognition (STAR) using many anonymous, binary sensors, in: International Conference on Pervasive Computing, 2005, pp. 62–79.
[63] M.C. Mozer, The neural network house: An environment that adapts to its inhabitants, in: Proc. AAAI Spring Symp. Intell. Environ. 1998, pp. 110–114.
[64] N. Roy, A. Misra, D. Cook, Ambient and smartphone sensor assisted ADL recognition in multi-inhabitant smart environments, J. Ambient. Intell. Humaniz. Comput. 7 (1) (2016) 1–19.
[65] B. Byrom, M. McCarthy, P. Schueler, W. Muehlhausen, Brain monitoring devices in neuroscience clinical research: The potential of remote monitoring using sensors, wearables, and mobile devices, Clin. Pharmacol. Ther. 104 (1) (2018) 59–71, http://dx.doi.org/10.1002/cpt.1077.
[66] A. Tricoli, N. Nasiri, S. De, Wearable and miniaturized sensor technologies for personalized and preventive medicine, Adv. Funct. Mater. 27 (15) (2017).
[67] C. Wang, K. Xia, H. Wang, X. Liang, Z. Yin, Y. Zhang, Advanced carbon for flexible and wearable electronics, Adv. Mater. 31 (9) (2019).
[68] O. Banos, et al., MHealthDroid: A novel framework for agile development of mobile health applications, in: Ambient Assisted Living and Daily Activities, Cham, 2014, pp. 91–98, http://dx.doi.org/10.1007/978-3-319-13105-4_14.
[69] S. Scheurer, S. Tedesco, K.N. Brown, B. O'Flynn, Using domain knowledge for interpretable and competitive multi-class human activity recognition, Sensors (2020) 1–25, http://dx.doi.org/10.3390/s20041208.
[70] Z. Qin, Y. Zhang, S. Meng, K.R. Choo, Imaging and fusing time series for wearable sensor-based human activity recognition, Inf. Fusion 53 (2020) 80–87.
[71] J.L. Reyes-Ortiz, L. Oneto, A. Ghio, A. Samá, D. Anguita, X. Parra, Human activity recognition on smartphones with awareness of basic activities and postural transitions, in: Lect. Notes Comput. Sci. Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinforma, Vol. 8681, in: LNCS, 2014, pp. 177–184, http://dx.doi.org/10.1007/978-3-319-11179-7_23.
[72] S.R. Taghanaki, A. Etemad, Self-supervised wearable-based activity recognition by learning to forecast motion, 2020.
[73] C.A. Ronao, S.B. Cho, Human activity recognition with smartphone sensors using deep learning neural networks, Expert Syst. Appl. 59 (2016) 235–244, http://dx.doi.org/10.1016/j.eswa.2016.04.032.
[74] H. Yu, S. Cang, Y. Wang, A.review.of.sensor. selection, A review of sensor selection sensor devices and sensor deployment for wearable sensor-based human activity recognition systems, in: Ski. 2016-2016 10th Int. Conf. Softw. Knowl. Inf. Manag. Appl, (January) 2017, pp. 250–257, http://dx.doi.org/10.1109/SKIMA.2016.7916228.
[75] A. Ignatov, Real-time human activity recognition from accelerometer data using Convolutional Neural Networks, Appl. Soft Comput. 62 (2018) 915–922, http://dx.doi.org/10.1016/j.asoc.2017.09.027.
[76] O. Banos, M. Damas, H. Pomares, I. Rojas, M.A. Toth, O. Amft, A benchmark dataset to evaluate sensor displacement in activity recognition, UbiComp (2012) 1026–1035.
[77] C. Catal, S. Tufekci, E. Pirmit, G. Kocabag, On the use of ensemble of classifiers for accelerometer-based activity recognition, Appl. Soft Comput. 37 (2015) 1018–1022, http://dx.doi.org/10.1016/j.asoc.2015.01.025.
[78] B. Delporte, L. Perroton, T. Grandpierre, J. Trichet, Accelerometer and magnetometer based gyroscope emulation on smart sensor for a virtual reality application, Sens. Transducers. J 14 (2012) 32–47.
[79] H. Gjoreski, M. Gams, Activity/posture recognition using wearable sensors placed on different body locations, in: Proceedings of the IASTED International Conference on Artificial Intelligence and Soft Computing, ASC 2011, 2011, pp. 340–347, http://dx.doi.org/10.2316/P.2011.716-067.
[80] J. Pärkkä, M. Ermes, P. Korpipää, J. Mäntyjärvi, J. Peltola, I. Korhonen, Activity classification using realistic data from wearable sensors, Inf. Technol. Biomed. IEEE Trans. 10 (1) (2006) 119–128.
[81] S. Chernbumroong, S. Cang, A. Atkins, H. Yu, Elderly activities recognition and classification for applications in assisted living, Expert. Syst. Appl. 40 (5) (2013).
[82] A.J. Cook, G.D. Gargiulo, T. Lehmann, T.J. Hamilton, Open platform, eight-channel, portable bio- potential and activity data logger for wearable medical device development, Electr. Lett. 51 (21) (2015) 1641–1643.
[83] M. Nakamura, J. Nakamura, M. Shuzo, S. Warisawa, I. Yamada, Collaborative processing of wearable and ambient sensor system for health monitoring application, in: 2010 3rd International Symposium on Applied Sciences in Biomedical and Communication Technologies (ISABEL 2010), 2010, pp. 1–5.
[84] M. Georgi, C. Amma, T. Schultz, Recognizing hand and finger gestures with IMU based motion and EMG based muscle activity sensing, in: BIOSIGNALS 2015-8th Int. Conf. Bio-Inspired Syst. Signal Process. Proc. Part 8th Int. Jt. Conf. Biomed. Eng. Syst. Technol. BIOSTEC 2015, 2015, pp. 99–108, http://dx.doi.org/10.5220/0005276900990108.
[85] Y. Jia, Diatetic and exercise therapy against diabetes mellitus, in: Second International Conference on Intelligent Networks and Intelligent Systems, 2009, pp. 693–696.
[86] J. Yin, Q. Yang, J. Pan, Sensor based abnormal human activity detection, IEEE Trans. Knowl. Data Eng. 20 (8) (2008) 1082–1090.
[87] K.S. Gayathri, S. Elias, B. Ravindran, Hierarchical activity recognition for dementia care using Markov Logic, Netw. Ubiquit Comput. 19 (2015) 271–285, http://dx.doi.org/10.1007/s00779-014-0827-7.
[88] A.M. Tripathi, R.D. Baruah, S. Subbiah, Oil well drilling activities recognition using a hierarchical classifier, J. Pet. Sci. Eng. (2020) 107883, http://dx.doi.org/10.1016/j.petrol.2020.107883.
[89] G.A. Oguntala, et al., SmartWall: Novel RFID-enabled ambient human activity recognition using machine learning for unobtrusive health monitoring, IEEE Access 7 (2019) 68022–68033, http://dx.doi.org/10.1109/ACCESS.2019.2917125.
[90] L. Schrader, et al., Advanced sensing and human activity recognition in early intervention and rehabilitation of elderly people, J. Popul. Ageing. 13 (2) (2020) 139–165, http://dx.doi.org/10.1007/s12062-020-09260-z.
[91] P. Siirtola, H. Koskimäki, J. Röning, Personalizing human activity recognition models using incremental learning, in: ESANN 2018 - Proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, 2018, pp. 627–632.
[92] S. Ishimaru, H. Kensuke, K. Kai, K. Koichi, D. Andreas, Towards reading trackers in the wild: detecting reading activities by eog glasses and deep neural networks. in: Proceedings of the 2017 ACM International Joint Conference on Pervasive Computing and Ubiquitous Computing ACM International Symposium on Wearable Computers, 2017, pp. 704–711.
[93] G. Rene, et al., Deep neural network based human activity recognition for the order picking process. in: Proceedings of the 4th international Workshop on Sensor-based Activity Recognition and Interaction, 2017, pp. 1–6.
[94] N.B. Gaikwad, V. Tiwari, A. Keskar, N.C. Shivaprakash, Efficient FPGA implementation of multilayer perceptron for real-time human activity classification, IEEE Access 7 (2019) 26696–26706.
[95] Y. Yang, C. Hou, Y. Lang, D. Guan, D. Huang, J. Xu, Open-set human activity recognition based on micro-Doppler signatures, Pattern Recognit. 85 (2019) 60–69, http://dx.doi.org/10.1016/j.patcog.2018.07.030.
[96] A. Wang, S. Zhao, C. Zheng, J. Yang, G. Chen, C.Y. Chang, Activities of daily living recognition with binary environment sensors using deep learning: A comparative study, IEEE Sens. J. 21 (4) (2021) 5423–5433, http://dx.doi.org/10.1109/JSEN.2020.3035062.
[97] P. Bharti, D. De, S. Chellappan, S.K. Das, HuMAn: complex activity recognition with multi-modal multi-positional body sensing, IEEE Trans. Mob. Comput. 18 (4) (2019) 857–870.
[98] P. Lago, M. Matsuki, S. Inoue, Achieving single-sensor complex activity recognition from multi-sensor training data, 2020, pp. 1–17, ArXiv200211284v1 CsHC 26 2020, no. Figure 1.
[99] Z. He, Activity recognition from accelerometer signals based on wavelet-AR model, in: 2010 IEEE International Conference on Progress in Informatics and Computing, 2010, pp. 499–502, http://dx.doi.org/10.1109/PIC.2010.5687572.
[100] W. Xiao, Y. Lu, Daily human physical activity recognition based on kernel discriminant analysis and extreme learning machine, in: Mathematical Problems in Engineering, 2015.

[101] A. Wang, G. Chen, J. Yang, S. Zhao, C.-Y. Chang, A comparative study on human activity recognition using inertial sensors in a smartphone, IEEE Sens. J. 16 (11) (2016) 4566–4578.
[102] A. Wijekoon, N. Wirantunga, Personalised meta-learning for human activity recognition with few-data, in: 40th British Computer Society's Specialist Group on Artificial Intelligence (SGAI) Artificial Intelligence International Conference, Vol. 2020, No. December, 2020.
[103] C. Ho, A. Robinson, D. Miller, M. Davis, Overview of sensors and needs for environmental monitoring, Sensors 5 (1) (2008) 4–37.
[104] N. Ravi, D. Nikhil, P. Mysore, M.L. Littman, Activity recognition from accelerometer data, in: Proceedings of the Seventeenth Conference on Innovative Applications of Artifi- cial Intelligence (IAAI), 2005, pp. 1541–1546.
[105] F.R. Allen, E. Ambikairajah, N.H. Lovell, B.G. Celler, Classification of a known sequence of motions and postures from accelerometry data using adapted Gaussian mixture models, Physiol. Meas. 27 (10) (2006) 935, http://dx.doi.org/10.1088/0967-3334/27/10/001.
[106] M. Ermes, J. Pärkkä, J. Mäntyjärvi, I. Korhonen, Detection of daily activities and sports with wearable sensors in controlled and uncontrolled conditions, IEEE Trans. Inf. Technol. Biomed. 12 (1) (2008) 20–26, http://dx.doi.org/10.1109/TITB.2007.899496.
[107] A. Mannini, A.M. Sabatini, Machine learning methods for classifying human physical activity from on-body accelerometers, Sensors 10 (2) (2010) 1154–1175, http://dx.doi.org/10.3390/s100201154.
[108] O. Aziz, E.J. Park, G. Mori, S.N. Robinovitch, Distinguishing the causes of falls in humans using an array of wearable tri-axial accelerometers, Gait Posture 39 (1) (2014) 506–512, http://dx.doi.org/10.1016/j.gaitpost.2013.08.034.
[109] R. Jia, B. Liu, Human daily activity recognition by fusing accelerometer and multi-lead ECG data, in: 2013 IEEE International Conference on Signal Processing, Communica- Tion and Computing (ICSPCC 2013), 2013, pp. 1–4, http://dx.doi.org/10.1109/ICSPCC.2013.6664056.
[110] M.H.M. Noor, Z. Salcic, K.I.K. Wang, Ontology-based sensor fusion activity recognition, J. Ambient Intell. Humaniz. Comput. 11 (8) (2018) 3073–3087, http://dx.doi.org/10.1007/s12652-017-0668-0.
[111] M.F. Shaikh, Z. Salcic, K.I.-K. Wang, A.P. Hu, Bipedal gait model for precise gait recognition and optimal triggering in foot drop stimulator: A proof of concept, Med. Biol. Eng. Comput. (2018) http://dx.doi.org/10.1007/s11517-018-1810-7.
[112] D. Anguita, A. Ghio, L. Oneto, X. Parra, J. Reyes-Ortiz, A public domain dataset for human activity recognition using smartphones, in: 21th European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, ESANN, 2013, pp. 24–26.
[113] R. Chavarriaga, et al., The opportunity challenge: A benchmark database for on-body sensor-based activity recognition, Pattern Recognit. Lett. 34 (15) (2013) 2033–2042, http://dx.doi.org/10.1016/j.patrec.2012.12.014.
[114] D. Micucci, M. Mobilio, P. Napoletano, UniMiB SHAR: A Dataset for human activity recognition using acceleration data from smartphones, Appl. Sci. Switz. 7 (10) (2017) http://dx.doi.org/10.3390/app7101101.
[115] A. Reiss, D. Stricker, Introducing a new benchmarked dataset for activity monitoring, in: Proc. - Int. Symp. Wearable Comput. ISWC, 2012, pp. 108–109, http://dx.doi.org/10.1109/ISWC.2012.13.
[116] Y. Xue, L. Jin, A naturalistic 3D acceleration-based activity dataset amp; benchmark evaluations, in: 2010 IEEE International Conference on Systems, Man and Cybernetics, 2010, pp. 4081–4085, http://dx.doi.org/10.1109/ICSMC.2010.5641790.
[117] N. Kawaguchi, et al., HASC Challenge: Gathering large scale human activity corpus for the real-world activity understandings, in: ACM Int. Conf. Proceeding Ser, 2011, pp. 1–5, http://dx.doi.org/10.1145/1959826.1959853.
[118] B. Kaluza, S. Kozina, M. Lustrek, The activity recognition repository: Towards competitive benchmarking in ambient intelligence, AAAI Workshop - Tech. Rep. WS-12-05, 2012, pp. 44–47.
[119] E. Tapia, S. Intille, L. Lopez, K. Larson, The design of a portable kit of wireless sensors for naturalistic data collection, in: International Conference on Pervasive Computing, 2006, pp. 117–134.
[120] F. Hodgins, J. Macey, Guide to the Carnegie Mellon University Multimodal Activity (Cmu-Mmac) Database, CMU-RI-TR-08-22, 2009.
[121] P. Casale, O. Pujol, P. Radeva, Personalization and user verification in wearable systems using biometric walking patterns, Pers. Ubiquitous Comput. (2012) 563–580.
[122] M. Bächlin, et al., Wearable assistant for Parkinson's disease patients with the freezing of gait symptom, IEEE Trans. Inf. Technol. Biomed. Publ. IEEE Eng. Med. Biol. Soc. 14 (2) (2010) 436–444, http://dx.doi.org/10.1109/TITB.2009.2036165.
[123] A. Bulling, U. Blanke, B. Schiele, A tutorial on human activity recognition using body-worn inertial sensors, Comput. Surv. 46 (3) (2014) 1–33, http://dx.doi.org/10.1145/2499621.
[124] S. Inoue, N. Ueda, Y. Nohara, N. Nakashima, Recognizing and understanding nursing activities for a whole day with a big dataset, J. Inf. Process. (2016) 853–866.
[125] Hasc2010 corpus, 2021, http://hasc.jp (accessed Jun. 19, 2021).
[126] D. Cook, Learning setting-generalized activity models for smart spaces, IEEE Intell. Syst. 27 (2012) 32–38.
[127] G. Singla, D.J. Cook, M. Schmitter-Edgecombe, Recognizing independent and joint activities among multiple residents in smart environments, J. Ambient Intell. Hum. Comput. 1 (2010) 57–63.
[128] HASC, Hasc_Bdd, 2021, http://hasc.jp/HASC_BDD/index.html (accessed Jul. 10, 2021).
[129] Predicting parkinson's disease progression with smartphone data, 2021, https://www.kaggle.com/c/3300/download/Participant Description.xls (accessed Jul. 02, 2021).
[130] T. Stiefmeier, D. Roggen, G. Troster, Fusion of string-matched templates for continuous activity recognition, in: Wearable Computers, 2007 11th IEEE International Symposium on IEEE, 2007, pp. 41–44.
[131] M. Wirz, D. Roggen, G. Troster, Decentralized detection of group formations from wearable acceleration sensors, 2009.
[132] K. Forster, D. Roggen, G. Troster, Unsupervised classifier self- calibration through repeated context occurences: Is there robustness against sensor displacement to gain? in: Wearable Computers ISWC'09. International Symposium on, IEEE, 2009, pp. 77–84.
[133] S. Zhang, P. McCullagh, C. Nugent, H. Zheng, Activity monitoring using a smart phone's accelerometer with hierarchical classification, in: Proc. 2010 Sixth Int. Conf. Intell. Environ. Kuala Lumpur Malays. (2010) pp. 158–163.
[134] M. Espinilla, L. Martinez, J. Medina, C. Nugent, The experience of developing the UJAmI smart lab, IEEE Access 6 (2018) 34631–34642, http://dx.doi.org/10.1109/ACCESS.2018.2849226.
[135] Sussex, Sussex-huawei locomotion dataset, 2020, http://www.shl-dataset.org/dataset/ (accessed Oct. 09, 2020).
[136] B. Bruno, F. Mastrogiovanni, A. Sgorbissa, Wearable inertial sensors: Applications, challenges, and public test benches, IEEE Robot. Autom. Mag. 22 (3) (2015) 116–124, http://dx.doi.org/10.1109/MRA.2015.2448279.
[137] N. Sikder, A. Al Nahid, KU-HAR: AN open dataset for heterogeneous human activity recognition, Pattern Recognit. Lett. 146 (2021) 46–54, http://dx.doi.org/10.1016/j.patrec.2021.02.024.
[138] D. Triboan, L. Chen, F. Chen, Z. Wang, A semantics-based approach to sensor data segmentation in real-time activity recognition, Future Gener. Comput. 93 (2019) 224–236.
[139] B. Quigley, M. Donnelly, G. Moore, L. Galway, A comparative analysis of windowing approaches in dense sensing environments, Multidiscip. Digit. Publ. Inst. Proc. 2 (2018) 1245.
[140] O. Banos, J. Galvez, M. Damas, H. Pomares, I. Rojas, Window size impact in human activity recognition, Sensors 14 (4) (2014) 6474–6499.
[141] M.H.M. Noor, Z. Salcic, K.I.-K. Wang, Adaptive sliding window segmentation for physical activity recognition using a single tri-axial accelerometer, Pervasive Mob. Comput. (2016) 1–19, http://dx.doi.org/10.1016/j.pmcj.2016.09.009.
[142] K. Chen, D. Zhang, L. Yao, B. Guo, Z. Yu, Y. Liu, Deep learning for sensor-based human activity recognition: overview, challenges and opportunities, 2020, arxiv:2001.07416.
[143] A. Ferrari, D. Micucci, M. Marco, P. Napoletano, Handcrafted features vs residual networks for human activities recognition using accelerometer, 2019.
[144] R.T. Olszewski, C. Faloutsos, D.B. Dot, Generalized feature extraction for structural pattern recognition in time-series data, 2001.
[145] H. Castro, et al., All-inkjet-printed low-pass filters with adjustable cutoff frequency consisting of resistors, inductors and transistors for sensor applications, Org. Electron. 38 (2016) 205–212.
[146] C. Ma, A. Wang, G. Chen, C. Xu, Hand joints-based gesture recognition for noisy dataset using nested interval unscented Kalman filter with LSTM network, Vis. Comput. 34 (6–8) (2018) 1053–1063.
[147] F. Gu, K. Khoshelham, S. Valaee, J. Shang, R. Zhang, Locomotion activity recognition using stacked denoising autoencoders, IEEE Internet Things J. 5 (3) (2018) 2085–2093.
[148] He Hong, Y. Tan, W. Zhang, A wavelet tensor fuzzy clustering scheme for multi-sensor human activity recognition, Eng. Appl. Artif. Intell. 70 (2018) 109–122.
[149] J. Rafiee, M.A. Rafiee, F. Yavari, M.P. Schoen, Feature extraction of forearm EMG signals for prosthetics, Expert Syst. Appl. 38 (4) (2011) 4058–4067, http://dx.doi.org/10.1016/j.eswa.2010.09.068.
[150] F. Xiao, et al., A deep learning method for complex human activity recognition using virtual wearable sensors, in: Lect. Notes Comput. Sci. Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinforma, in: LNCS, vol. 12567, 2021, pp. 261–270, http://dx.doi.org/10.1007/978-3-030-69873-7_19.
[151] K. Shirahama, M. Grzegorzek, On the generality of codebook approach for sensor-based human activity recognition, Electronics 6 (2) (2017) 44.
[152] H. Abdi, L.J. Williams, Principal component analysis, Wiley Interdiscip. Rev. Comput. Stat. 2 (4) (2010) 433.

[153] L. Zhang, X. Wu, D. Luo, Human activity recognition with HMM-DNN model, in: 2015 IEEE 14th International Conference on Cognitive Informatics & Cognitive Computing (ICCI*CC), 2015, pp. 192–197, http://dx.doi.org/10.1109/ICCI-CC.2015.7259385.

[154] E. Fridriksdottir, A.G. Bonomi, Accelerometer-based human activity recognition for patient monitoring using a deep neural network, Sensors 20 (22) (2020) 6424.

[155] C.A. Ronao, S.B. Cho, Human activity recognition with smartphone sensors using deep learning neural networks, Expert Syst. Appl. 59 (2016) 235–244, http://dx.doi.org/10.1016/j.eswa.2016.04.032.

[156] W. Gao, L. Zhang, Q. Teng, J. He, H. Wu, DanHAR: DUal attention network for multimodal human activity recognition using wearable sensors, Appl. Soft Comput. 111 (2021) 107728.

[157] H. Khaled, O. Abu-Elnasr, S. Elmougy, A.S. Tolba, Intelligent system for human activity recognition in IoT environment, Complex Intell. Syst. (2021) 1–12.

[158] S.S. Saha, S.S. Sandha, M. Srivastava, Deep Convolutional Bidirectional LSTM for Complex Activity Recognition with Missing Data, 199, No. November, Springer Singapore, 2021, http://dx.doi.org/10.1007/978-981-15-8269-1_4.

[159] M.N. Haque, M. Mahbub, M.H. Tarek, L.N. Lota, A.A. Ali, Nurse care activity recognition: A GRU-based approach with attention mechanism, in: Adjunct Proceedings of the 2019 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2019 ACM International Symposium on Wearable Computers, 2019, pp. 719–723.

[160] J. Pan, Z. Hu, S. Yin, M. Li, GRU With dual attentions for sensor-based human activity recognition, Electronics 11 (11) (2022) 1797.

[161] D. Arifoglu, A. Bouchachia, Activity recognition and abnormal behaviour detection with recurrent neural networks, Procedia Comput. Sci. 110 (2017) 86–93.

[162] H. Nair, C. Tan, M. Zeng, O.J. Mengshoel, J.P. Shen, AttriNet: LEarning mid-level features for human activity recognition with deep belief networks, in: Adjunct Proceedings of the 2019 Acm International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2019 ACM International Symposium on Wearable Computers, 2019, pp. 510–517.

[163] M.M. Hassan, S. Huda, M.Z. Uddin, A. Almogren, M. Alrubaian, Human activity recognition from body sensor data using deep learning, J. Med. Syst. 42 (6) (2018) 99, http://dx.doi.org/10.1007/s10916-018-0948-z.

[164] M.H.M. Noor, Feature learning using convolutional denoising autoencoder for activity recognition, Neural Comput. Appl. 33 (17) (2021) 10909–10922, http://dx.doi.org/10.1007/s00521-020-05638-4.

[165] M.H.M. Noor, M.A. Ahmadon, M.K. Osman, Activity recognition using deep denoising autoencoder, in: Proc. - 9th IEEE Int. Conf. Control Syst. Comput. Eng. ICCSCE 2019, 2019, pp. 188–192, http://dx.doi.org/10.1109/ICCSCE47578.2019.9068571.

[166] X. Gao, H. Luo, Q. Wang, F. Zhao, L. Ye, Y. Zhang, A human activity recognition algorithm based on stacking denoising autoencoder and lightGBM, Sensors 19 (4) (2019) 947.

[167] Y. Kwon, K. Kang, C. Bae, Unsupervised learning for human activity recognition using smartphone sensors, Expert Syst. Appl. 41 (14) (2014) 6067–6074, http://dx.doi.org/10.1016/j.eswa.2014.04.037.

[168] O. Nafea, W. Abdul, G. Muhammad, Multi-sensor human activity recognition using CNN and GRU, Int. J. Multimedia Inf. Retr. 11 (2) (2022) 135–147.

[169] M.H. Mohd Noor, S.Y. Tan, M.N. Ab Wahab, Deep temporal conv-LSTM for activity recognition, Neural Process. Lett. (2022) 1–23.

[170] Z. Lin, M. Li, Z. Zheng, Y. Cheng, C. Yuan, Self-attention convlstm for spatiotemporal prediction, in: Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 34 (07) 2020, pp. 11531–11538.

[171] H. Qian, S.J. Pan, B. Da, C. Miao, A novel distribution-embedded neural network for sensor-based activity recognition, in: IJCAI Int. Jt. Conf. Artif. Intell., Vol. 2019-Augus, 2019, pp. 5614–5620, http://dx.doi.org/10.24963/ijcai.2019/779.

[172] S. Sani, N. Wiratunga, S. Massie, K. Cooper, kNN sampling for personalised human recognition, in: Proceedings of the 25th International Case-Based Reasoning Conference, Robert Gordon University, Aberdeen, 2017, pp. 330–344.

[173] M.T. Uddin, M.A. Uddiny, A guided random forest based feature selection approach for activity recognition, in: 2nd International Conference on Electrical Engineering and Information and Communication Technology, ICEEiCT 2015, 2015, pp. 1–6, http://dx.doi.org/10.1109/ICEEICT.2015.7307376.

[174] K.G. Manosha Chathuramali, R. Rodrigo, Faster human activity recognition with SVM, in: Int. Conf. Adv. ICT Emerg. Reg. ICTer 2012 - Conf. Proc, 2012, pp. 197–203, http://dx.doi.org/10.1109/ICTer.2012.6421415.

[175] L. Fan, Z. Wang, H. Wang, Human activity recognition model based on decision tree, in: 2013 International Conference on Advanced Cloud and Big Data, 2013, pp. 64–68, http://dx.doi.org/10.1109/CBD.2013.19.

[176] Y. LeCun, Y. Bengio, G. Hinton, Deep learning, Nature 521 (2015) 436–444.

[177] M. Zeng, T. Yu, X. Wang, L.T. Nguyen, O.J. Mengshoel, I. Lane, Semi-supervised convolutional neural networks for human activity recognition, in: Proc. - 2017 IEEE Int. Conf. Big Data Big Data 2017, 2018-Janua, 2017, pp. 522–529, http://dx.doi.org/10.1109/BigData.2017.8257967.

[178] T. Plotz, Y. Guan, Deep learning for human activity recognition in mobile computing, Computer 51 (5) (2018) 50–59, http://dx.doi.org/10.1109/MC.2018.2381112.

[179] T. Nusrat, I. Mahbubul, B. Joong-Hwan, Deep learning-based action recognition using 3D skeleton joints information, Inventions 5 (49) (2020) 1–15, http://dx.doi.org/10.3390/inventions5030049.

[180] G. Ascioglu, Y. Senol, Design of a wearable wireless multi-sensor monitoring system and application for activity recognition using deep learning, IEEE Access 8 (2020) 169183–169195, http://dx.doi.org/10.1109/ACCESS.2020.3024003.

[181] F. Demrozi, G. Pravadelli, A. Bihorac, P. Rashidi, Human activity recognition using inertial, physiological and environmental sensors: A comprehensive survey, IEEE Access 8 (Dl) (2020) 210816–210836, http://dx.doi.org/10.1109/ACCESS.2020.3037715.

[182] I. Perez-Pozuelo, D. Spathis, E.A.D. Clifton, C. Mascolo, Wearables, smartphones, and artificial intelligence for digital phenotyping and health, Digit. Health 54 (2021) 33–54, http://dx.doi.org/10.1016/b978-0-12-820077-3.00003-1.

[183] N.Y. Hammerla, S. Halloran, T. Plötz, Deep, convolutional, and recurrent models for human activity recognition using wearables, in: IJCAI Int. Jt. Conf. Artif. Intell., Vol. 2016-Janua, 2016, pp. 1533–1540.

[184] D. Wu, Z. Wang, Y. Chen, H. Zhao, Mixed-kernel based weighted extreme learning machine for inertial sensor based human activity recognition with imbalanced dataset, Neurocomputing 190 (2016) 35–49.

[185] S. Ranasinghe, F. Al MacHot, H.C. Mayr, A review on applications of activity recognition systems with regard to performance and evaluation, Int. J. Distrib. Sens. Netw. 12 (2016).

[186] X. Li, P. Zhao, M. Wu, Z. Chen, L. Zhang, Deep learning for human activity recognition, Neurocomputing 444 (2021) 214–216, http://dx.doi.org/10.1016/j.neucom.2020.11.020.

[187] S.R. Ramamurthy, N. Roy, Recent trends in machine learning for human activity recognition—A survey, Wiley Interdiscip. Rev. Data Min. Knowl. Discov. 8 (4) (2018) http://dx.doi.org/10.1002/widm.1254.

[188] P. Gupta, P. Caleb-Solly, A Framework for Semi-Supervised Adaptive Learning for Activity Recognition in Healthcare Applications, Vol. 893, Springer International Publishing, 2018, http://dx.doi.org/10.1007/978-3-319-98204-5_1.

[189] J. Wen, M. Zhong, J. Indulska, Creating general model for activity recognition with minimum labelled data, in: ISWC 2015 - Proc. 2015 ACM Int. Symp. Wearable Comput, 2015, pp. 87–90, http://dx.doi.org/10.1145/2802083.2808399.

[190] D. Balabka, Semi-supervised learning for human activity recognition using adversarial autoencoders, in: UbiComp/ISWC 2019- - Adjunct Proceedings of the 2019 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2019 ACM International Symposium on Wearable Computers, 2019, pp. 685–688, http://dx.doi.org/10.1145/3341162.3344854.

[191] S. Mohamad, M. Sayed-Mouchaweh, A. Bouchachia, Online active learning for human activity recognition from sensory data streams, Neurocomputing 390 (2020) 341–358, http://dx.doi.org/10.1016/j.neucom.2019.08.092.

[192] S. Oh, A. Ashiquzzaman, D. Lee, Y. Kim, J. Kim, Study on human activity recognition using semi-supervised active transfer learning, Sensors 21 (8) (2021) http://dx.doi.org/10.3390/s21082760.

[193] P. Bota, J. Silva, D. Folgado, H. Gamboa, A semi-automatic annotation approach for human activity recognition, Sens. Switz. 19 (3) (2019) 1–23, http://dx.doi.org/10.3390/s19030501.

[194] A. Saeed, T. Ozcelebi, J. Lukkien, Multi-task self-supervised learning for human activity detection, in: Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 3 (2) 2019, pp. 1–30.

[195] C.I. Tang, I. Perez-Pozuelo, D. Spathis, C. Mascolo, Exploring contrastive learning in human activity recognition for healthcare, in: Machine Learning for Mobile Health Workshop at NeurIPS 2020, 2020, pp. 1–6.

[196] N. Weber, Unsupervised learning in human activity recognition: A first foray into clustering data gathered from wearable sensors, no. February, 2016.

[197] T. Sheng, M. Huber, Unsupervised embedding learning for human activity recognition using wearable sensor data, in: Proceedings of the 33rd International Florida Artificial Intelligence Research Society Conference, FLAIRS 2020, 2020, pp. 478–483.

[198] A. Mohamed, G.E. Dahl, H. Geoffrey, Acoustic modeling using deep belief networks, IEEE Trans. Audio Speech Lang. Proc. 20 (1) (2011) 14–22.

[199] T.W. Liao, Clustering of time series data— A survey, Pattern Recognit. 38 (11) (2005) 1857–1874.

[200] D.H. Fisher, Knowledge acquisition via incremental conceptual clustering, Mach. Learn. 2 (1987) 139–172.

[201] M.G. Omran, A.P. Engelbrecht, A. Salman, An overview of clustering methods, Intell. Data Anal. 11 (2007) 583–605.
[202] T. Kohonen, Self-Organizing Maps, Springer, 1997.
[203] D.B. Fogel, Evolutionary Computation: Toward a New Philosophy of Machine Intelligence, John Wiley & Sons, Hoboken, NJ, USA, 2006.
[204] B. Schölkopf, A.J. Smola, K.R. Müller, Nonlinear component analysis as a kernel eigenvalue problem, Neural Comput. 10 (1998) 1299–1319.
[205] M. Iwayama, T. Tokunaga, Cluster-based text categorization: A comparison of category search strategies, in: In Proceedings of the 18th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, 1995, pp. 273–280.
[206] T.F. Gonzalez, Clustering to minimize the maximum intercluster distance, Theoret. Comput. Sci. 38 (1985) 293–306, http://dx.doi.org/10.1016/0304-3975(85)90224-5.
[207] H.-S. Park, C.-H. Jun, A simple and fast algorithm for K-medoids clustering, Expert Syst. Appl. 36 ((2) Part 2) (2009) 3336–3341, http://dx.doi.org/10.1016/j.eswa.2008.01.039.
[208] R.T. Ng, J. Han, CLARANS: A method for clustering objects for spatial data mining, IEEE Trans. Knowl. Data Eng. 14 (5) (2002) 1003–1016, http://dx.doi.org/10.1109/TKDE.2002.1033770.
[209] T. Zhang, R. Ramakrishnan, M. Livny, BIRCH: An efficient data clustering method for very large databases, ACM Sigmod Rec. 25 (2) (1996) 103–114.
[210] S. Guha, R. Rastogi, K. Shim, ROCK: A Robust clustering algorithm for categorical attributes, Inf. Syst. 25 (5) (2000) 345–366.
[211] D. Miljković, Brief review of self-organizing maps, in: 2017 40th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO), 2017, pp. 1061–1066, http://dx.doi.org/10.23919/MIPRO.2017.7973581.
[212] S. Mirjalili, Genetic algorithm, Evol. Algorithms Neural Netw. (2019) 43–55, http://dx.doi.org/10.1007/978-3-319-93025-1_4.
[213] I.S. Dhillon, Y. Guan, B. Kulis, Kernel k-means: spectral clustering and normalized cuts, in: Proceedings of the Tenth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2004, pp. 551–556, http://dx.doi.org/10.1145/1014052.1014118.
[214] C. Dobbins, R. Rawassizadeh, Towards clustering of mobile and smartwatch accelerometer data for physical activity recognition, Informatics 5 (2) (2018) 29, http://dx.doi.org/10.3390/informatics5020029.
[215] D. Trabelsi, S. Mohammed, F. Chamroukhi, L. Oukhellou, Y. Amirat, An unsupervised approach for automatic activity recognition based on hidden Markov model regression, IEEE Trans. Autom. Sci. Eng. 10 (3) (2013) 829–835, http://dx.doi.org/10.1109/TASE.2013.2256349.
[216] Y. Kwon, K. Kang, C. Bae, Unsupervised learning for human activity recognition using smartphone sensors, Expert Syst. Appl. 41 (14) (2014) 6067–6074, http://dx.doi.org/10.1016/j.eswa.2014.04.037.
[217] S. Kafle, D. Dou, A heterogeneous clustering approach for human activity recognition, in: Lect. Notes Comput. Sci. Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinforma, in: LNCS, vol. 9829, 2016, pp. 68–81, http://dx.doi.org/10.1007/978-3-319-43946-4_5.
[218] H. Ma, Z. Zhang, W. Li, S. Lu, Unsupervised human activity representation learning with multi-task deep clustering, in: Proc. ACM Interact. Mob. Wearable Ubiquitous Technol., Vol. 5 (1), 2021, pp. 1–25, http://dx.doi.org/10.1145/3448074.
[219] H. He, Y. Tan, J. Huang, Unsupervised classification of smartphone activities signals using wavelet packet transform and half-cosine fuzzy clustering, in: 2017 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), 2017, pp. 1–6, http://dx.doi.org/10.1109/FUZZ-IEEE.2017.8015566.
[220] L.F. Mejia-Ricart, P. Helling, A. Olmsted, Evaluate action primitives for human activity recognition using unsupervised learning approach, in: 2017 12th International Conference for Internet Technology and Secured Transactions, ICITST 2017, 2018, pp. 186–188, http://dx.doi.org/10.23919/ICITST.2017.8356374.
[221] K. Jun, S. Choi, Unsupervised end-to-end deep model for newborn and infant activity recognition, Sensors 20 (22) (2020) 6467, http://dx.doi.org/10.3390/s20226467.
[222] L. Bai, C. Yeung, C. Efstratiou, M. Chikomo, Motion2Vector: UNsupervised learning in human activity recognition using wrist-sensing data, in: Adjunct Proceedings of the 2019 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2019 ACM International Symposium on Wearable Computers, 2019, pp. 537–542, http://dx.doi.org/10.1145/3341162.3349335.
[223] A. Abedin, F. Motlagh, Q. Shi, H. Rezatofighi, D. Ranasinghe, Towards deep clustering of human activities from wearables, in: Proceedings of the 2020 International Symposium on Wearable Computers, 2020, pp. 1–6, http://dx.doi.org/10.1145/3410531.3414312.
[224] O. Konak, P. Wegner, J. Albert, B. Arnrich, Unsupervised activity recognition using trajectory heatmaps from inertial measurement unit data, 2022, http://dx.doi.org/10.5220/0010838800003116.
[225] E. Brophy, Z. Wang, Q. She, T. Ward, Generative adversarial networks in time series: A survey and taxonomy, 2021, arXiv:2107.11098.
[226] I.J. Goodfellow, et al., Generative adversarial nets, Adv. Neural Inf. Process. Syst. 3 (January) (2014) 2672–2680, http://dx.doi.org/10.3156/jsoft.29.5_177_2.
[227] P. Santiago, B. Antonio, S. Joan, SEGAN: SPeech enhancement generative adversarial network, 2017, arXiv:1703.09452.
[228] P. Ofir, B. Amir, B. Ben, B. Jonathan, W. Lior, Language generation with recurrent generative adversarial networks without pre-training, 2017, arXiv:1706.01399, 2017.
[229] J. Wang, Y. Chen, Y. Gu, Y. Xiao, H. Pan, SensoryGANs: An effective generative adversarial framework for sensor-based human activity recognition, in: Proceedings of the International Joint Conference on Neural Networks, 2018, http://dx.doi.org/10.1109/IJCNN.2018.8489106, 2018-July, 1–8.
[230] K. Gray, D. Smolyak, S. Badirli, G. Mohler, Coupled IGMM-GANs for deep multimodal anomaly detection in human mobility data, 2018, arXiv Prepr. arXiv:1809.02728.
[231] J. Donahue, P. Krahenbuhl, T. Darrell, Adversarial feature learning, 2016, arXiv Prepr. arXiv:1605.09782.
[232] L. Qi, C. Liang, S. Changqing, Y. Bingru, Z. Zhongkui, Enhanced generative adversarial networks for fault diagnosis of rotating machinery with imbalanced data, Aust. J. Mech. Eng. 18 (1) (2020) 119–123, http://dx.doi.org/10.1080/14484846.2018.1432089.
[233] X. Li, J. Luo, R. Younes, ActivityGAN: Generative adversarial networks for data augmentation in sensor-based human activity recognition, in: UbiComp/ISWC 2020 Adjunct - Proceedings of the 2020 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2020 ACM International Symposium on Wearable Computers, 2020, pp. 249–254, http://dx.doi.org/10.1145/3410530.3414367.
[234] M. Alzantot, S. Chakraborty, M. Srivastava, SenseGen: A Deep learning architecture for synthetic sensor data generation, in: 2017 IEEE International Conference on Pervasive Computing and Communications Workshops, PerCom Workshops 2017, 2017, pp. 188–193, http://dx.doi.org/10.1109/PERCOMW.2017.7917555.
[235] F. Alharbi, L. Ouarbya, J.A. Ward, Synthetic sensor data for human activity recognition, in: Proceedings of the International Joint Conference on Neural Networks, Vol. July, 2020, http://dx.doi.org/10.1109/IJCNN48605.2020.9206624.
[236] M.H. Chan, M.H.M. Noor, A unified generative model using generative adversarial network for activity recognition, J. Ambient Intell. Humaniz. Comput. (2020) http://dx.doi.org/10.1007/s12652-020-02548-0.